A METHODOLOGY FOR DEMAND ASSESSMENT AND INTEGRATED SCHEDULE DESIGN AND FLEET ASSIGNMENT APPLIED TO THIN-HAUL SCHEDULED OPERATIONS

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A METHODOLOGY FOR DEMAND ASSESSMENT AND INTEGRATED SCHEDULE DESIGN AND FLEET ASSIGNMENT APPLIED TO THIN-HAUL SCHEDULED OPERATIONS

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Aos meus pais José e Maria, e à minha irmã Marina

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SUMMARY

The thin-haul market is characterized by short-range routes with low demand, occasionally served by commuter airlines. Historically, commuter operators have not been able to maintain profitable operations in this market, migrating to longer and more profitable routes throughout the years. As a result, many small cities have lost their air service and airports have become underutilized. Aiming to change this scenario, many studies have focused on the development of vehicle technologies to promote thin-haul scheduled operations and the assessment of potential demand. This thesis investigates thin-haul operations from the airline's point of view, aiming to understand how flight operations optimization can aid commuter operators to improve profitability and, ultimately, to restore the air service to small communities.

Despite the low individual demand of each thin-haul route, an opportunity for profitability may exist if the origin-destination pairs are effectively served. This can be achieved if the airline makes the right schedule decisions, i.e., strategically defines when and where to fly, as well as the assignment of the aircraft with the right capacity to the right flight leg. These problems are part of the schedule planning process and are known in the literature as schedule design and fleet assignment (SD&FA). However, the lack of historical data and baseline schedule for thin-haul operations imposes challenges for demand estimation and SD&FA applications.

Therefore, the contribution of this thesis is in the development of a methodology for demand assessment and integrated SD&FA applied to thin-haul operations that can overcome the aforementioned challenges. This is achieved by investigating thin-haul demand based on the competition with alternative modes of transport and by coupling the current SD&FA techniques with the concept of hourly demand distribution. The proposed methodology is implemented in a framework that allows different operational scenarios to be evaluated based on the operations metrics of effectiveness, which includes the airline profit, the po-

tential thin-haul demand served, and the passenger time savings. Such framework enables stakeholders to understand the key elements that lead to profitable thin-haul operations, the extent to which the air service can be expanded, and the potential benefits for passengers and cities. The experiments conducted in this thesis demonstrated that the methodology can successfully perform SD&FA applied to thin-haul operations and determine the *true market share*, i.e., the potential demand that can be profitably served by an air carrier. Additional case studies highlighted that more efficient operations can be achieved if airlines adopt a mix of point-to-point and connecting flights, and that hub location and aircraft attributes can significantly impact the effectiveness of the operations.

CHAPTER 1

INTRODUCTION AND MOTIVATION

1.1 Commuter Airlines and the Thin-Haul Market

The early stages of the airline industry development was characterized by a focus on technological advancements and deep government involvement in airline competition [1]. During this period, policies heavily regulated airlines' economic and operational affairs. In the United States, part of this public intervention addressed the concern expressed by small communities regarding their location far from major airports, which could result in limited access to air service. Federal agencies established subsidized scheduled airline service to communities with population density too small to produce enough air demand volume, forcing airlines to use revenue from profitable routes to provide service to low-volume ones [2]. The service, however, was still limited, only supplying flights to major airports and often at inconvenient times.

After the economic deregulation process that started in the USA in the 60's [3], free market was established, with cost efficiency and profitability becoming the central issues in airline management [1]. Under this new competitive scenario, carriers became free to make their own business decisions, being able to set prices and serve the routes they saw fit. Large airlines abandoned most of the short-range, low-volume routes and migrated to more profitable markets with higher demand, since subsidized jet service to small cities was no longer mandatory. As a result, air service in these communities experienced a steady decline. To fill this gap, a new category of carriers called *commuter airlines* started to fly these low-volume routes using turboprop aircraft with seat capacities of less than 60 seats, connecting these small cities to large hubs [2–4]. In addition, the government determined that a selected number of cities should be subjected to the "Essential Air Service" (EAS) program, which provided subsided air service using public investments. The number of EAS points, however, decreased from 468 in 1978 to about 115 in the contiguous states, limiting even more the access to air service throughout the years [4, 5].

These trends shaped the current topology of air transportation in the USA, with most of the demand and air service being concentrated on relatively few routes connecting major cities in the country. These routes are usually served by large carriers such as Delta and United Airlines using wide-body aircraft. The network is complemented by regional airlines serving routes that connect secondary economic centers using regional jets, such as Skywest Airlines. Lastly figures the *thin-haul market*, comprised of low-volume routes with short flight ranges varying from 50 to 350 miles. This segment is occasionally served by commuter operators flying ultra-short routes using small capacity aircraft and small regional airlines connecting cities to major hubs [6], as shown in Figure 1.1.

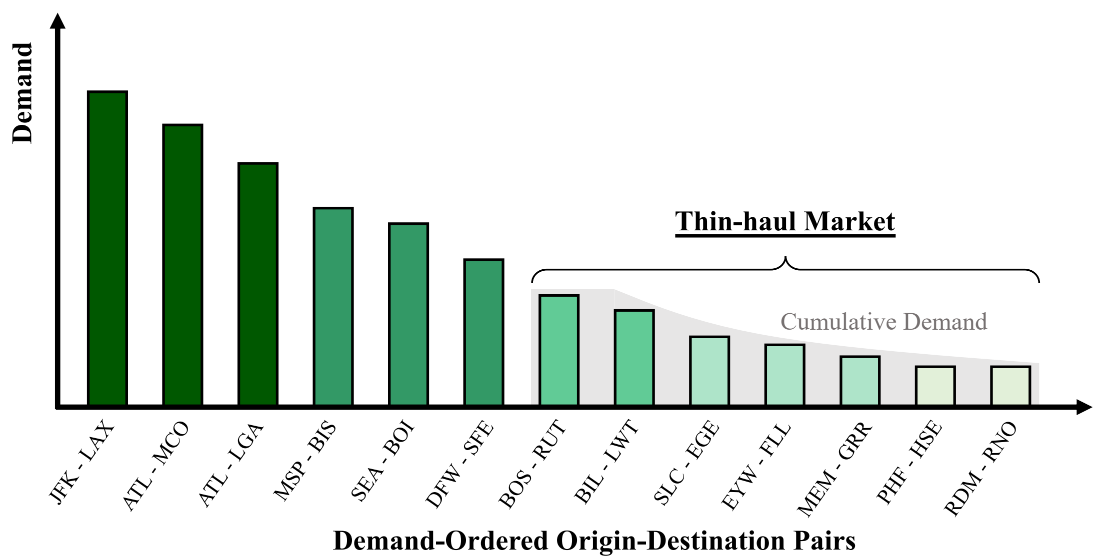


Figure 1.1: Notional of common origin and destination pairs (adapted from [6])

Despite the limited demand for each individual origin and destination (O&D) pair in the thin-haul market, the cumulative demand across the entire network can be significant [6, 7]. A potential may exist for profitability if the demand of all O&D pairs are efficiently served using commuter aircraft. Additionally, because time is highly important for business trips, many small cities have made significant investments in local airports to attract general aviation and scheduled air service, concerned that the absence of air transportation would hinder their economic development [2]. Most of this public investment, however, has not been used by the population. Currently only about 500 out of 19,500 airports receive commercial air service, that reaches only ten percent of the network of public airports [7, 8]. With most of these public airports remaining underutilized, there is a lot of available infrastructure with government support that can be used by future commuter airlines. Ultimately, thin-haul operations present advantages over typical commercial carriers, such as not being subjected to complete security checks at airports, which improves the travel time of passengers [9, 10].

Nonetheless, despite the potential demand and available infrastructure, commuter operators have not recently experienced high growth rates and significant profitability; on the contrary, commuter airlines seem hesitant to expand operations [6]. In fact, many short-haul markets have witnessed a decline in the number of flights in the past decade. Once again, most of the airlines serving short-range markets have migrated to more profitable routes, abandoning the service in markets that were no longer economical and reducing even more the number of communities with air service [11].

One of the main challenges faced by commuter airlines to keep or expand operations is the high operating cost when trying to serve a low-volume and scattered demand [7]. With fewer efficient small aircraft available in the market, commuter fleet became composed of obsolete aircraft with expensive maintenance cost that often do not have enough passengers to breakeven their costs and generate revenue. As a consequence, airlines have been retiring aircraft with less than 50 seats to acquire larger and modern jets with better cost per seat mile and passenger acceptance to fly denser routes [11]. For instance, the number of flights covered by typical 19-seat vehicles has substantially decreased in North America in the past 20 years, from almost 1,500 departures in 1998 to less than 250 in 2018 [12].

Another challenge relies on the trade-off between reducing travel time and increasing passenger volume at hubs. Most commuter carriers adopt a hub-and-spoke network, concentrating operations in one or two regional airports and offering flights to major hubs only. Passengers are usually forced to take multiple flights to travel to most destinations, even those less than 300 miles away. These circuitous routes are detrimental to passengers' door-to-door travel time, especially when passengers from small communities are forced to travel 50 to 100 miles to the airport. This has impacted the transportation mode chosen by passengers to travel short and medium distances. A survey conducted by the American Travel Survey (ATS) revealed that three-quarters of the trips between 200 and 800 miles were done using automobiles [2]. Air service became the preferable mode only for trips over 800 miles. Concentrating travelers at fewer airports may allow more profitable operations, but it is unattractive time-wise. Consequently, airlines end up losing passengers to ground transportation.

Therefore, these challenges associated to high operating costs, sparse demand, and competition with alternative modes of transportation need to be overcome in order to promote the thin-haul market. If successful, airlines would be able to expand their operations, develop new routes, and serve this latent demand in small communities, reducing the commuting time and bringing economic development to these regions.

One of the first efforts in this direction was conducted by NASA through the Small Aircraft Transportation System (SATS) program in the early 2000 [13]. The goal of this program was to enhance general aviation (GA) using new technologies in aircraft engines, pilot training, avionics, and communication systems to increase air service access in small airports and improve door-to-door travel time. According to NASA, the SATS would adopt inexpensive all-weather aircraft for on-demand, air taxi, business, and scheduled operations, offering affordable air service to the public. The studies within the program targeted the impact that future SATS operations could have on the air traffic system, as well as the estimation of the existent latent demand in the USA that chooses the mode of transportation mostly based on time considerations [14–16]. Long et al. [14] developed a demand model to estimate air traffic at the airport level based on historical GA operations, using a gravity model to predict the traffic between airports that serves as an input to a Monte Carlo simulation used to generate flights. Trani et al. [15] proposed a systems dynamics model to analyze feasibility of SATS from a life-cycle point of view, performing demand estimation and network analysis to understand the future impact of SATS in the number of flights operating in the US airports. Ashiabor et al. [16] estimated demand for SATS considering passenger mode choice between cars and commercial service, also incorporating airport-choice. The analysis, however, was limited to 443 airports that already had commercial service, and did not bring any potential solution to overcome the current challenges.

Other authors proposed solutions to reverse the unfavorable scenario in the thin-haul market focused on the advancement of new technologies in electric propulsion and how it can enable the expansion of thin-haul commercial operations. Short-range routes provide the ideal scenario for electric propulsion applications, since current battery technology limits the range of electric and hybrid-electric aircraft. The use of electric propulsion in the commuter fleet can significantly reduce the energy expenditure of commuter operators, therefore reducing the operating cost [7]. Antcliff et al. [17] proposed the conceptual design of a parallel hybrid-electric version of the ATR 42-500 with multiple propulsors, aiming to decrease the operating cost by lowering the energy required to complete a given mission. Similarly, Stoll et al. [18] developed a conceptual design study of a distributed electric propulsion aircraft serving thin-haul routes. Harish et al. [6] investigated both the operational and economic impacts of introducing a fleet of distributed electric propulsion aircraft into the operations of a commuter airline. Justin et al. [7] also investigated the reductions in the operating cost when using electric aircraft, discussing strategies to optimize battery recharge and ensure benefits from the low cost of electricity. Weit et al. [9] developed a network-optimized vehicle that maximizes the profit of a commuter airline through the optimization of the hybridization level, using a notional network from Cape Air.

These studies focused mainly on analyzing the thin-haul market in the vehicle-level, airport-level, and from an air traffic management perspective, along with potential demand assessment. The *airline operations level* and how strategic operations decisions can promote economically viable thin-haul operations have not been widely addressed in the literature yet. Even though the previous studies suggested that the cumulative demand in the thin-haul market could be significant, there is not much evidence that this demand can yield profitable operations. In other words, the *true market share*, i.e., the potential demand that can be profitably served by an air carrier, has not yet been investigated. Nonetheless, to achieve successful thin-haul operations, airlines must be able to reduce the door-to-door travel time of passengers in order to effectively capture the demand of short-range routes that is currently served by ground transportation. These observations are summarized as follows:

Observation 1: *Most studies estimate the potential thin-haul demand, but they do not demonstrate that the demand is significant enough to sustain profitable thin-haul operations.*

Observation 2: *Successful commercial service in the thin-haul market needs to reduce the door-to-door travel time of passengers over short-range routes when compared to ground transportation.*

Observation 3: *There is a lack of studies investigating thin-haul operations from the airline perspective.*

Therefore, to understand how thin-haul operations can be improved and expanded effectively, demand assessment needs to be performed accounting for competition with ground transport, while the analysis of flight operations requires an airline-centered approach that aims to maximize airline gains. Flight operations are usually modeled using two different approaches: simulation methods and Operations Research (OR) techniques.

Agent-based simulation has been used in air transportation problems to understand how individual agents such as passengers, airlines, airports, and regulatory agencies behave and interact with each other. In this case, agents change their decisions based on the behavior of other agents in the system. It is often used to understand air traffic congestion, simulate flight delays, schedule interruptions, and the impact of changes in regulations on the agents decisions [19, 20]. These interactions have mostly non-linear nature. Since airlines seek optimum operations to maximize their gains, finding a global solution of an agent-based simulation is typically challenging and often ineffective, requiring advanced methods for optimization.

Operations Research, on the other hand, focuses on the airline perspective and applies analytical methods for problem-solving and decision-making to ensure that air carriers adopt the right business strategy that maximizes their profitability. OR techniques, specially linear programming, network analysis and assignment problems, have been widely used by carriers in their strategic operations decisions, helping the airline industry to manage the continuous increase in passenger demand and to sustain high growth rates over the years [21]. In this context, OR may allow commuter airlines to build a successful business model and to tackle the challenge of serving the thin-haul scattered demand profitably. Therefore, OR is the most suitable approach to analyze airline operations in the thin-haul market, considering its focus on improving airline effectiveness and the linear nature of its optimization models. OR techniques applied to the airline industry are further discussed in the following section.

1.2 Airline Operations Research

The logistics behind the airline industry are highly complex, composed by a net of activities interacting to each other in different levels. These activities are correlated to an extensive number of affairs, including market assessment, airline staffing, crew and maintenance schedule, aircraft routing, fleet assignment, revenue management, aviation safety, among others. Since airlines typically operate under marginal profit [22], a minor disruption in any of these elements may lead to a chain reaction with significant economic impacts that could result in economic non-viability.

Therefore, airlines are continually striving to optimize their operations and use their assets as effectively as possible, seeking to address all the aforementioned aspects simultaneously. Special attention is given to schedule planning, which involves the development of suitable aircraft and crew schedules to maximize profit and minimize operating cost [21]. In other words, to operate efficiently, airlines need to know the best schedule to serve a certain demand, the set of aircraft that should be allocated to a certain route, and the crew assigned to the right flight, i.e., *"putting the right plane with the right number of seats and the right crew on the right route at the right time"* [23].

Attempting to solve a full schedule planning may lead to a highly complex and unmanageable problem. To circumvent this issue, the schedule planning is commonly divided in four topics [21]: (1) *schedule design*, which defines when and where to fly, i.e., determines the schedule and frequency of flights to serve a certain market; (2) *fleet assignment*, aimed at determining which aircraft type should be assigned to each flight leg; (3) *aircraft routing*, that specifies the maintenance rotations of the fleet; and finally (4) *crew scheduling*, that defines which crew should be allocated to each flight. These four sub-problems are also closely correlated to the demand estimation task, which provides information regarding the market share and therefore dictates the city pairs to be served and the flight frequency. Revenue management completes the process, defining fare levels, and how many seats should be available at each fare [1]. Figure 1.2 depicts the main elements of the schedule planning and the iterative sequential approach that they follow.

Figure 1.2 shows that demand assessment and schedule design are the preliminary steps in the schedule planning process, followed by the fleet assignment problem. The latter plays a central role since it interacts significantly with the other elements, but mainly with schedule design, aircraft routing, and revenue management [24]. Because they represent the starting point and the core of the schedule planning process, respectively, most researchers focus on solving the schedule design and the fleet assignment sub-problems. Besides, both

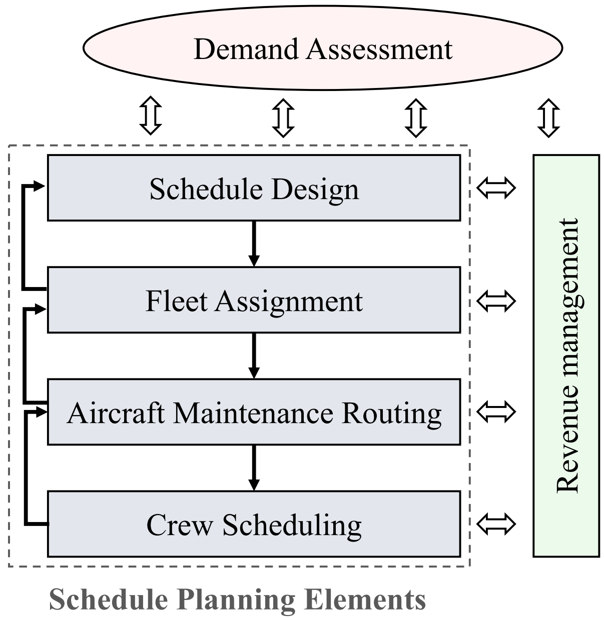


Figure 1.2: Typical airline schedule planning process (adapted from [24])

sub-problems are correlated, i.e., the decisions regarding frequency of flights and fleet employment are interdependent [24]. Many different methodologies have been developed to tackle the prodigious amount of variables involved in these two sub-problems when solved simultaneously or not. In these formulations, two major approaches are considered: the *warm start approach* and the *cold start approach* [24]. The first one performs schedule design by making incremental adjustments to a previous similar schedule. The *cold start approach* is adopted when there is no previous schedule. The majority of methodologies, however, are based on the *warm start approach*, since building a new schedule is computationally challenging and requires data that is often not available. The main methodologies developed to solve the schedule design and the fleet assignment (SD&FA) are detailed in section 2.2, as well as their applications to the airline industry.

1.3 Problem Statement

Airlines serving the thin-haul market can also benefit from Operation Research techniques. An efficient placement of flights, assets, and crew may increase the odds for economic viability in this sector. A proper fleet assignment can increase the load factor and ensure that the fleet is able to bear its operating cost, one of the major challenges for commuter airlines. The understanding of thin-haul demand and passenger behavior, allied with the development of an efficient schedule to serve most of the potential demand, can allow increase in revenue. All of these elements need to be captured simultaneously so strategic decisions such as where and when to fly can be made in order to achieve successful operations.

Nonetheless, there have not been many studies focused on OR applied to thin-haul operations. Using OR techniques in a decision-making environment can assist stakeholders in understanding under which circumstances profitable thin-haul operations can be achieved. Therefore, the main purpose of this research is to build a *decision-making framework* that allows the assessment of metrics of effectiveness for thin-haul operations based on a set of inputs and operations decisions. In the context of the thin-haul market, these metrics of effectiveness are mainly related to the identification of *profitable routes* and the *true market share*. Integrating passenger demand estimation with scheduling planning allows the understanding of the potential market share for thin-haul operations and how much of this market can be successfully served when combined with electric and hybrid-electric aircraft. Since schedule design and fleet assignment (SD&FA) are the main elements in the schedule planning process, an appropriate methodology capturing these two components and passenger demand is needed. This leads to the objective of this research:

Research Objective: *To investigate the economic viability of thin-haul operations by developing a framework that accounts for passenger demand and integrated airline schedule design and fleet assignment.*

The aforementioned research objective raises questions about how passenger demand assessment and airline SD&FA can be performed for thin-haul operations, and how these elements can be integrated in the same framework. The first step is to understand the passenger demand behavior in the thin-haul market. It represents a crucial aspect since the low-volume characteristic of thin-haul routes is one of the main reasons of the decrease in air service in this market. Besides, the lack of historical data for the thin-haul market and the competition against ground transport present atypical challenges that need to be considered. The decision-making framework needs to be able to capture the potential market share, how it varies under different economic parameters and operations decisions, and how these aspects impact the performance of thin-haul operations. Thus, the first research question is:

> **RQ1:** *How can passenger demand be accounted for to support thin-haul operations decisions?*

The following step lies on performing the SD&FA. The methodology needs to carry out these two analyses considering passenger demand behavior and thin-haul operations aspects. This leads to the second research question:

> **RQ2:** *How can schedule design and fleet assignment be performed for thin-haul operations?*

Finally, in addition to capture the aforementioned elements, as a decision-making tool, the framework must allow the evaluation of different scenarios and concept of operations. The operations effectiveness needs to be quantified under different strategic decisions, which leads to the last research question:

> **RQ3:** *How can the concept of operations to effectively serve the thin-haul market be determined?*

The following chapter describes the main studies regarding passenger demand estimation, schedule design and fleet assignment and how the research objective and the research questions are addressed in this thesis. Chapter 4 describes the methodology development, while chapter 4 details the hypothesis testing. Chapter 5 brings the results of different case studies and chapter 6 draws the conclusions of this thesis.

CHAPTER 2
THESIS ARGUMENTS

This chapter summarizes the main approaches from the literature that could be adopted to address the research questions and discusses the limitations in the current methodologies. Subsequently, strategies are proposed to answer each one of these research questions.

2.1 Thin-Haul Passenger Demand Estimation

RQ1: *How can passenger demand be accounted for to support thin-haul operations decisions?*

2.1.1 Literature Review

Most of the traditional demand forecasting techniques are composed of qualitative methods, time-series projections, causal methods, and gravity models [22]. Except for the latter, all of them require air service historical data as input, which is not available for the thin-haul market. Moreover, airlines serving this market compete against alternative modes of transportation, which impacts how demand should be estimated. Few authors have approached this competition between air and ground transport, mainly focused on Urban Air Mobility (UAM) and on-demand thin-haul operations [14–16, 25–29].

Due to the inter-modal nature of this competition, the current methodologies are based on the *four-step model* (FSM) [30], characterized by a *trip-based* demand modeling approach. This approach is based on the definition of two correlated systems: one with socioeconomic, demographic, and land use data, and the other with transport network information, which provides data about the transportation infrastructure and the nodes and links that compose the network. The FSM is a sequential formulation used to simplify the complex interaction between these systems in a realistic application. As depicted in Figure 2.1, the first step, trip generation, specifies trip frequency of origin or destination trips depending on the trip purpose. In the trip distribution step, trips are matched to origin and destination pairs based on trip attractiveness. The mode choice step predicts the mode of transportation that individuals will choose to make the trip, defining the proportion of trips for each O&D pair covered by a particular mode. In the last step, trip assignment (or route choice), allocates trips of an specific mode to routes, i.e., determines the routes travellers will choose to reach the destination and the flow of passengers at each route. Route allocation affects network flows, which influence the trip assignment, leading to an iterative process until convergence is reached.

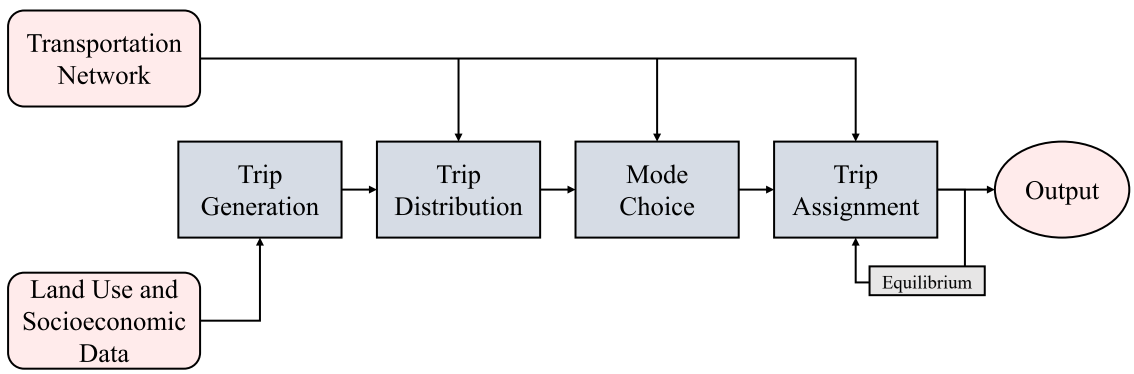


Figure 2.1: The four-step approach (adapted from [30])

The majority of studies adopts the first three steps of the FSM to estimate the demand of UAM, on-demand, and scheduled air service considering the competition with ground transport, with emphasis on the mode choice step. Among those, one of the first studies was the one developed by Ashiabor et al. [16], that assessed the demand for SATS using a multinomial logit (MNL) model in the mode choice step to determine the probability P_i of a passenger choosing the mode i, as shown in Equation 2.1. MNL models are commonly used to estimate passenger decisions based on utility functions that relate different parameters and are derived for the available options. Individuals choose the alternative mode that maximizes his or her utility. Equation 2.2 exemplifies an utility function u_i in which X_{ij} is the j variable in the model and α_j is the respective coefficient, that is estimated through calibration using available data.

$$P_i = \frac{e^{u_i}}{\sum_i e^{u_i}} \tag{2.1}$$

$$u_i = \alpha_j X_{ij} \tag{2.2}$$

In their work, Ashiabor et al. [16] adopted travel time, travel cost, household income, and the origin and destination locations as variables to compare two modes of transport: automobiles and SATS. Trip generation and distribution were defined at the county level using the National Travel Survey (NTS). Airport choice was incorporated to the mode choice to estimate both market share in the county level and the market share between airlines offering different routes, i.e., in the airport-to-airport level. The airport-to-airport trips were converted to flights using a time-of-day profile based on scheduled data retrieved from the Official Airline Guide (OAG). OAG data was also used to calibrate the choice model, along with the DB1B and the NTS databases. One of the limitations of their methodology, however, is that only the 443 airports that had commercial service were considered. This work complemented the study conducted by Trani et al. [15], mainly improving the approach adopted in the mode choice step. As a result, the authors were able to forecast future demand at airports with the introduction of SATS, which is relevant to policy makers and airport management.

Pu et al. [26] also adopted an MNL model to study the potential market of an electric commuter aircraft for on-demand service. In their research, the authors addressed the competition between automobile, transit, and on-demand air transportation, represented by the commuter aircraft. The utility functions were developed considering in-vehicle travel time, out-of-vehicle travel time, and travel cost. The models for automobile and transit were calibrated for seven metropolitan areas using the National Household Travel Survey database, considering only work trips; recreation trips and commuter journey greater than $100\ nmi$ were excluded. These baseline models were calibrated multiple times to account for different income group levels. The model for the commuter aircraft was initially developed with deterministic parameters, but it was further calibrated using different values of out-of-vehicle time to better predict behavior considering different distance to airports, and also different air travel costs.

Kreimeier et al. [28], on the other hand, estimated the potential market of on-demand air mobility (ODAM) in Germany by addressing the competition against automobiles with a different approach to determine the mode split. The preference for each mode of transport was derived based on the trip cost and time and the income patterns of the passengers. For ODAM service, time and cost were computed including the ingress and the egress portions of the trip. The ODAM transportation mode was compared to automobiles using an *opportunity cost* function, that was computed considering the ratio between the cost difference and the travel time difference between the two modes. In this context, the opportunity cost reflects a monetary value per hour that future passengers must be able to afford to switch to a faster mode, in this case represented by the ODAM vehicle. This opportunity cost was then contrasted to the income level of the passengers to determine the market share of ODAM and automobiles for each trip. Trip generation and distribution were conducted by first determining feasible airfields and the number of people living in a certain distance to the airfields. From this subset, the flow of passengers from one airfield to another was computed adopting a gravity model, calibrated using census and transportation data.

Adopting the same concept of opportunity cost defined by Kreimeier et al. [28] to compute the mode split, Paproth et al. [29] were one of the few authors to propose a methodology to estimate potential demand for thin-haul scheduled operations in Germany. In the first step of their approach, trip generation and distribution were performed by selecting routes covered by ground transport with distance over 100km from traffic flow databases. For each one of these routes, the cost and time to cover the trip was estimated for five modes of transport: car, intercity bus, intercity train, commercial aircraft, and thin-haul air mobility service. Time and cost of thin-haul air service also accounted for ingress, egress, and the flight portions of the trip. Cost and time differences between two modes of transport were then contrasted using the opportunity cost, that was compared to the income level of passengers with different trip purposes to estimate the market share of the modes of transport considered in the analysis.

Nonetheless, the methodologies proposed by Pu et al. [26], Kreimeier et al. [28], and Paproth et al. [29] require detailed trip data that is often not available in most cities and countries. To circumvent that, Mayakonda et al. [27] proposed a methodology to estimate UAM demand worldwide by determining the total addressed market based on the total ground-based passenger traffic in a city, represented by the passenger kilometers (PKM) traveled. The UAM market share was then computed in terms of PKM. The mode choice was determined based on the traveler's willingness to pay (WTP) for a trip using an UAM vehicle. The WTP was estimated considering the passengers value of travel time savings (VTTS), the time saved when using UAM, and the cost of using an alternative mode of transport. The VTTS was a function of the travelers income and the trip purpose. The WTP was then compared to the cost of the trip using an UAM vehicle to identify viable UAM trips and estimate the total volume of ground traffic for those trips. The authors estimated the number of trips produced by the analyzed metropolitan area using demographic data, and the total PKM and the UAM PKM using socioeconomic data of the affected population, based on their WTP.

In general, these methodologies can be grouped in two main approaches that represent potential alternatives to assess thin-haul demand considering the competition with ground transport and answer **RQ1**. The **first group** makes a direct comparison between two modes of transport by computing the *opportunity cost*. The income level of the passengers is then used to determine the market share based on the potential of passengers to afford or be willing to switch to air service. The **second group** uses MNL models to determine the utilities of each one of the available modes of transport to cover a trip and computes the market share considering that passengers want to maximize their utilities. In this case, trip cost and time are often the parameters of the utility function. Historical data, as well as socioeconomic factors, are used to calibrate the coefficients of the models. Regardless of the approach adopted, the aforementioned methodologies demonstrated the relevance that price difference, time savings, and socioeconomic factors have in the mode choice of passengers traveling short-range routes.

However, while the approach used by previous authors to perform the steps of trip generation and trip distribution can be directly applied in this research, these two main alternatives to compute mode choice present some limitations. The published studies focus on determining the potential market share (or mode split), i.e., the total number of passengers willing to fly a certain route. They do not determine the market that can be viably served by scheduled air service, i.e., the *true market share*. In order to determine it, the potential demand needs to be investigated considering airline schedule and operations decisions. To do so, passenger demand estimation to support thin-haul operations needs to account not just for the potential demand of the routes, but also captures passenger behavior depending on different available itineraries that airlines will likely offer for each route. Nonetheless, one of the few approaches that targets demand estimation of thin-haul scheduled operations, proposed by Paproth et al. [29], lacks the element of itinerary choice.

Other authors developed approaches to predict passenger preference among itineraries outside the thin-haul scope, most of them adopting MNL models. For instance, Lurkin et al. [31, 32] proposed a model to capture individuals trade-offs among different itineraries considering the following attributes: total trip time, number of connections, departure time of the day, ticket price, distance of itinerary, direction of travel, number of time zones crossed, and departure time of the week. The model was developed for continental U.S. markets using a database of 10 million trips provided by Airlines Reporting Corporation for calibration. The size of the database allowed the estimation of highly refined departure time preferences. The model also accounted for price endogeneity, i.e., when price is influenced by demand, resulting in higher prices when demand is high and vice-versa.

Results suggested that passengers strongly prefer non-stop flights, and that departure time is more relevant for passengers traveling short-haul trips (lower than 600 miles), with distinct peaks in the mornings and afternoons. Socioeconomic data, however, was not considered in the analysis.

MNL models are also often used to determine the *itinerary attractiveness*, a concept first proposed by Wang et al. [33] on their methodology for airline planning process. In this case, the probability that a passenger chooses any itinerary of a route is equal to the ratio of its attractiveness to the total attractiveness of all other alternatives, also including itineraries from other airlines. This concept was integrated to classic schedule planning and network design models described in the following section, defining the market share of an itinerary as a decision variable while also proportional to its attractiveness. In this way, airline schedule and operations decisions are made considering passenger choice for itineraries.

Nonetheless, although MNL models can be adopted to predict passenger behavior at the itinerary level, these methods require massive data for calibration to achieve accurate results. Besides, the potential demand of routes, i.e., the mode split, often needs to be well known. Because of that, when determining itinerary choice, MNL models are mainly applied to existing airlines that are already in service or markets that have consolidated historical data.

In light of these observations, in order to answer **RQ1**, thin-haul passenger demand estimation needs to:

- Quantify the potential market share of thin-haul operations when compared to alternative modes of transport;
- Quantify passenger demand at the itinerary level considering the main elements in thin-haul operations that influence passenger choice.

The absence of a methodology for thin-haul passenger demand that tackles these two elements simultaneously leads to the first research gap:

Gap RQ1: Current studies investigating thin-haul demand focus on determining the potential market share, without approaching the demand at itinerary-level needed to support scheduling decisions and determine the true market share.

2.1.2 Hypothesis and Experiments

As previously mentioned, the current methodologies that could be adopted to answer **RQ1** can be grouped in two main alternatives: **Alternative 1**, that adopts the concept of opportunity cost to determine the mode split as proposed by Kreimeier et al. [28] and Paproth et al. [29], and **Alternative 2**, represented by MNL models that rely on utility functions to determine the mode split but can also be used to compute itinerary choice, as proposed by Ashiabor et al. [16] and other authors. Although the opportunity cost approach is relatively straightforward to implement, it presents lower fidelity than MNL models by not accounting for itinerary options. On the other hand, the MNL approach is a high fidelity technique that can be used to determine both mode and itinerary choice, but requires massive data for calibration and robust data science tools to be accurately implemented, and it is often a time-consuming and computationally expensive approach.

Under these circumstances, a method to estimate passenger demand to support thin-haul operations needs to determine both mode split and itinerary choice and to overcome the lack of data for calibration, while keeping medium fidelity and reasonable implementation time. Based on these considerations, it is possible to set the requirements that the approach must meet to answer **RQ1**. These requirements define the criteria to evaluate the current and proposed methodologies:

Criteria RQ1: capturing both potential market and itinerary choice, need for calibration data, fidelity level, implementation time.

As Alternatives 1 and 2 may not meet the established criteria to answer **RQ1**, the research gap can be addressed if these alternatives are integrated while tackling the drawbacks of each existing method. In this context, the opportunity cost approach can be adopted to compute the mode split at the *itinerary level*, defining the share of passengers that would be willing to switch from ground transportation to any of the available itineraries. In order words, it defines which itineraries passengers can afford based on their income. This first step ensures that time, cost, and socioeconomic factors, the three main parameters that drive passenger's decisions in the thin-haul market, are considered. The fidelity of the results can be improved by adopting a simplified version of the MNL model. This version defines which choices are more attractive to passengers based on the itineraries they can afford, using a utility function defined by only one parameter that therefore do not require calibration. The final result, that represents the *itinerary attractiveness*, can be determined by combining the results of both steps. In others words, this is equivalent to integrating Alternative 1 with a simplified version of Alternative 2. With this proposed methodology, that represents **Alternative 3**, the *itinerary attractiveness* of each itinerary can be determine, along with the mode split of each route.

Thus, the three potential alternatives to answer **RQ1** can be summarized as follows:

Alternative 1: methodology proposed by Paproth et al. [29] and Kreimeier et al. [28] that determines the mode split by comparing the opportunity cost to the passengers' income distribution.

- *Pros*: Not computationally expensive or time-consuming, no need for calibration;
- *Cons*: Not done at the itinerary level, lower fidelity.

Alternative 2: methodology proposed by Ashiabor et al. [16] and other authors that adopts MNL models to determine the mode split and the itinerary attractiveness.

- *Pros*: High fidelity, can be adopted to compute both mode split and itinerary attractiveness;

- *Cons*: Time consuming, computationally expensive, requires massive data for calibration.

Alternative 3: new methodology that combines the opportunity cost and income distribution with a one-parameter utility function to determine the itinerary attractiveness and to estimate demand at itinerary-level.

- *Pros*: Defines both mode split and itinerary attractiveness, no need for calibration data, medium fidelity, not time-consuming, not computationally expensive;

Based on the pros and cons of each alternative, the new methodology represented by Alternative 3 is expected to best meet the criteria established to answer **RQ1**. This claim can be stated as a hypothesis:

HP1: *If* choice of mode and itinerary attractiveness techniques are combined, while accounting for competition with alternative modes of transport, *then* thin-haul passenger demand at the itinerary-level can be quantified with medium fidelity.

To substantiate **HP1**, it is necessary to demonstrate that alternatives 1 and 2 do not yield satisfactory results or have prohibited implementation, and that the proposed approach is the one that best meets the established criteria. Due to its high fidelity, the first attempt is to adopt MNL models to compute both mode choice and itinerary demand, as described by Alternative 2. In this case, the opportunity cost is the parameter of the utility function that drives passengers decisions. A second effort is to extend the method proposed by Alternative 1 to the itinerary-level. Lastly, the proposed methodology is tested against the criteria. Summarizing, to test **HP1**, the following set of experiments is proposed:

- For a sample of routes, considering a hybrid network with point-to-point and connecting flights that results in multiple itineraries for each route:

    1. **Testing Alternative 2** - using the concept of opportunity cost and a typical utility function used in MNL models similar to Equation 2.2, attempt to determine

the potential market share and the itinerary attractiveness. Compute the attractiveness assuming different coefficient values in the utility function. Demonstrate that the mode split in this case is not properly defined, that the coefficient assumptions highly affect the results, and therefore calibration is required;

2. **Testing Alternative 1** - adapt Alternative 1, considering the concept of opportunity cost along with the income distribution to determine the mode split at the itinerary level. Demonstrate it yields low fidelity, inaccurate results;

3. **Testing Alternative 3** - use Alternative 1 to determine the mode split at the itinerary level. Improve the results by adopting an utility function that does not require calibration, i.e., that depends on only one parameter, to compute the *sub-attractiveness* of the itineraries. Combine the results to determine the *itinerary attractiveness* and demand at itinerary level. Indicate that the results meet the established criteria.

The previous experiments are expected to demonstrate that the results from MNL models rely on the accuracy of the coefficients estimation, and therefore requires reliable data for calibration. In the case of thin-haul operations, this type of data is either unavailable or outdated. The approach represented by Alternative 1, on the other hand, presents poor fidelity when directly applied at the itinerary-level. If successful, these experiments will increase the confidence in the need for a new method based on different elements from alternatives 1 and 2 that does not need data for calibration while keeping medium level of fidelity, as defined in **HP1**. In addition, the experiments should demonstrate the method successfully determines the mode split and the attractiveness at itinerary-level considering income patterns within reasonable implementation time.

2.2 Schedule Design and Fleet Assignment Applied to Thin-Haul Operations

RQ2: *How can schedule design and fleet assignment be performed for thin-haul operations?*

2.2.1 Literature Review

Many authors have tackled the fleet assignment problem and its interaction with schedule design [23, 24, 33–47]. Among the first researchers to propose a computational solution for a large-scale basic *Fleet Assignment Model* (FAM) were Hane et al. [40]. They were the first to propose the concept of a *time-space network*, that uses nodes and arcs to represent aircraft position at a certain time. This network representation became widely used by many subsequent authors. The basic FAM aims to minimize the assignment cost, and it is subjected to four main constraint sets: cover constraints, which force each flight leg to be flown by exactly one aircraft type; balance constraints, which entail flow conservation at each airport; through constraints, that connect an inbound flight at an airport with an outbound flight at the same airport using the same aircraft; and at last the fleet size constraints, which count the number of aircraft of each type used by the solution. Their methodology established the ground for many future studies that were developed mainly to improve two main weaknesses in the basic FAM: the requirement for fixed departure times and the *flight-based* or *leg-based* approach adopted in their model.

In reality, airlines may experience schedule disturbances, such as small delays, changes to improve passenger connections, or gate availability issues. Deriving the fleet assignment from a fixed schedule can lead to inefficient employment of assets and revenue losses. On the other hand, adopting a leg-based approach means that demand and revenue of a flight are independent of the other flights in the schedule. In practice, both are defined at the O&D level or at the itinerary-level and a flight can be part of different itineraries [24]. Network effects, mainly the spill cost and recaptured revenue components, are usually only approximated, which can ultimately lead to sub-optimal solutions. Spill cost is defined as the loss of revenue when an aircraft type is assigned to a flight without being able to accommodate all the passenger demand. In its turn, recapture is the term used when the airline spills some of these remaining passengers to one of its own flights. Both effects directly affect the cost and revenue of the airline, and therefore its net profit.

Focusing on improving the departure time of the flights, Rexing et al. [41] proposed a version of the basic FAM allowing certain flexibility in the departures. In their approach, a time window was assigned to each flight departure in the schedule and then discretized according to a certain time interval. Copies of the flight arcs were created in each of these intervals, and the algorithm was set to choose which of these flights arcs to fly, requiring that only one of the copies should be covered. Thus, flight departures were characterized by time windows instead of fixed times, allowing the algorithm to choose more cost effective departures. Desaulniers et al. [42] followed a similar approach, but instead of creating copies of flight arcs, the flight departure times t_{if} were allowed to vary within a time-window [a_{if}, b_{if}]. By allowing this variance, the authors were able to increase the connection possibilities of the basic FAM.

Aiming to improve the leg-based approach, Barnhart et al. [43] proposed an extension of the basic FAM considering *network effects*, i.e., modeling spill and recapture as a function of the assigned capacity across an entire airline network instead of just a single flight leg. The *Itinerary-Based Fleet Assignment Model* (IFAM) combines the basic FAM with the *Passenger Mix Model (PMM)*, which takes a fleeted schedule (that is, each flight leg is already assigned to one aircraft type), and unconstrained itinerary demand as inputs and finds the flow of passengers over this schedule that maximizes fleeting contribution.

Complementing Barnhart et al. work [43], Lohatepanont et al. [44] introduced a model for the *Integrated Schedule Design and Fleet Assignment* (ISD-FA), considering the interaction between demand and supply of flights. The model takes as inputs a list with mandatory and optional flights and the unconstrained demand of each itinerary. Flights from the mandatory list must be assigned to one aircraft type, while flights from the optional list may be assigned or may be deleted from the schedule. If a flight is removed, the demand of each market is adjusted using demand correction terms. The selection of flight legs among the mandatory and optional flights and the fleet assignment are simultaneously optimized, following the same approach as the IFAM to consider spill and recapture effects.

Although the preliminary results from Barnhart et al. [43] demonstrated that incorporating network effects can significantly impact the revenue, their approach was based on a fixed recapture rate that was independent of the itineraries available in the market. In practice, passenger preference among the available itineraries may differ, which can significantly impact the network effects. As previously mentioned, Wang et al. [33] proposed an approach considering *passenger choice* based on the *attractiveness* of the itineraries in the market, that were composed not only by the options offered by the host carrier, but also by other airlines. The attractiveness is usually modeled as a utility function that captures the itinerary attributes such as departure time, duration of flight, number of stops, and ticket price. In their methodology, the authors defined the market share of each itinerary as a design variable and linked it to the ISD-FA proposed by Lohatepanont et al. [44]. Given the demand of a market, the share of each itinerary serving the market is determined by the algorithm proportionally to its attractiveness.

Passenger choice was also considered by Cadarso et al. [45] in their approach to perform schedule design while capturing the multimodal competition between an existent high-speed rail, low-cost airlines, and legacy airlines. The competition was represented by a nested logit model that was calibrated using data from two airlines and a rail company in Europe. Yan et al. [46] also used a MNL model to represent passenger behavior and integrated it to the ISD-FA approach proposed by Lohatepanont et al. [44], along with a network revenue management problem (NRM). In this case, passengers choose to buy fare products belonging to a market according to certain probabilities that depend on the set of fare products being offered. The solution proposed by Lohatepanont et al. [44] to the

ISD-FA model was improved by partitioning flights into partly separable sub-networks.

Despite the advances in the proposed methodologies to tackle the problem of concurrent SD&FA, the previous studies have a common disadvantage: they are based on the *warm-start approach*. Due to the high computational requirements to solve an ISD-FA coupled with passenger choice considerations, these methods focus on incremental timetabling approaches by relying on small changes in schedule or selection of flights. Independently of the method used, the formulation is derived upon a baseline schedule, usually from the airline previous season.

Nonetheless, because the thin-haul market mostly includes small communities that have not experienced air service in many years or at all, there is no historical data or baseline schedule to perform the typical ISD-FA using the warm start approach. Therefore, SD&FA for thin-haul operations needs to follow the cold start approach. One of the few studies that adopts this approach is the one developed by Wei et al. [47]. In their study, the authors proposed an integrated timetabling development and fleet assignment model (ITD-FA) to perform schedule design from a clean slate considering a discrete-choice generalized attraction model. Their methodology captures passengers' decisions using the MNL model developed by Lurkin et al. [31, 32] to compute the attractiveness of the itineraries, similarly to what is proposed by Wang et al. [33]. As aforementioned, in this case the market share of each itinerary was defined as a design variable. Itineraries were determined based on the O&D pair, fare class, and passenger type, usually grouped as business and leisure travelers. In addition to the constraints of the basic FAM, other sets of constraints established that passengers can change itineraries based on the attractiveness and aircraft capacity limitations, and that all itinerary market shares within the same O&D pair added to one. Another constraint limited the frequency of flights of each market considering the user input. The objective function was the profit, set to be maximized. Itineraries from other airlines and the no-fly option were also included, although the no-fly alternative was ignored due to the lack of available data or research studies.

The utility function adopted by the authors to determine the itinerary attractiveness accounts for the highly refined departure time preferences computed by Lurkin et al. [31, 32], used to perform the schedule design. Wei et al. [47] then proposed to divide a day of operations in discrete time periods of 15 minutes, each one representing a possible flight, letting the model to decide the most appropriate departure time based on the attractiveness of the itineraries. They tested the approach using data from Alaska Airlines in five different sets of networks containing 5 to 59 airports, with a maximum of 390 flights. To reduce the magnitude of the problem, they used a multi-phase framework coupled with a series of heuristics approaches that considered either a fleeted network or symmetry of flights in the segments. The authors compared the results with the main methodologies that adopt the warm start approach and observed improvements in profit that varied from 10% to 57%, with running time oscillating from 2h to 48h.

Nonetheless, although the ITD-FA model proposed by Wei et al. [47] adopts the cold start approach, this method also requires historical data from aviation. Their approach relies on the utility functions developed by Lurkin et al. [31, 32] to compute the attractiveness of the itineraries. As mentioned before, these utility values relate itinerary attributes such as trip time, cost, distance, and departure time preference, which drives the schedule design. This model, however, was constructed based on massive historical data from flight bookings around the world, which is also unavailable for thin-haul operations. SD&FA applied for thin-haul operations, on the other hand, must rely on travel patterns observed from trips covered using ground transport, since those are the passengers that airlines serving the thin-haul market aim to capture. These considerations lead to the second research gap:

Gap RQ2: Current studies focused on airline schedule design and fleet assignment problems require either a baseline schedule or passenger preference for departure time as an input, which are not available for the thin-haul market. There is no current methodology that integrates SD&FA with time preference based on ground transport to support thin-haul operations decisions.

2.2.2 Hypothesis and Experiments

Similarly to the studies of thin-haul passenger demand, the aforementioned methodologies for integrated schedule design and fleet assignment that could be used to answer **RQ2** can be grouped in three main alternatives. **Alternative 1** encompasses those methodologies that adopts the basic FAM allowing small changes in departure time as proposed by Rexing et al. [41] and Desaulniers et al. [42]. **Alternative 2** represents those methods based on the itinerary-based ISD-FA model proposed by Lohatepanont et al. [44]. Lastly, **Alternative 3** includes the ITD-FA model proposed by Wei et al. [47].

As previously mentioned, although widely adopted in different airline problems, the methods represented by Alternatives 1 and 2 require baseline schedule as an input, which is prohibitive for thin-haul operations. On the other hand, although the approach represented by Alternative 3 does not require baseline schedule, it relies on the MNL models developed by Lurkin et al. [31] to define passenger preference for departure time, which drives the schedule decisions in the model. However, these MNL models were developed using massive historical data from aviation bookings. As previously mentioned, for thin-haul operations this type of data is unavailable. Besides, schedule decisions should be driven by departure time preference from passengers using ground transport to cover short-range trips, since this is the demand airlines wish to capture.

Furthermore, the MNL models developed by Lurkin et al. [31] also account for the other itinerary attributes such as total trip time, number of connections, and ticket price, combined with the departure time. In this context, in the methodology proposed by Wei et al. [47], passengers' departure time preference is *coupled* to the other itinerary attributes to build the attractiveness model considered in the analysis. If a similar approach is adopted to analyze thin-haul operations, every time schedule decisions are evaluated under a different input for departure time preference, the attractiveness model must be re-calculated. However, passenger's departure time preference may vary significantly depending on the competing mode of transport used to cover the trip or between different O&D pairs and regions. For a decision-making framework designed to investigate thin-haul operations under different scenarios, a more flexible approach is desirable. Ideally, the formulation of the SD&FA model applied to thin-haul operations must allow departure time preference to be *decoupled* from the other itinerary attributes so different trip patterns can be easily investigated.

Another limitation of the ITD-FA model is the freedom passengers have to switch itineraries based on their attractiveness. Although Alternative 3 allows recaptured revenue to be accurately considered, the passengers willingness to pay for a trip and therefore their income levels are highly relevant for the thin-haul market, as demonstrated by many authors in section 2.1. In this case, passengers will not freely change itineraries; they may be able to afford one option but not the other. The SD&FA model applied to thin-haul operations has to overcome this limitation without substantially undermining the accuracy of the results. Ultimately, the model is also expected to overcome the computational challenges faced by Wei et al. [47] that prevented the application in large networks, considering the potential size of the thin-haul network due to the amount of airports without commercial air service in the USA.

Therefore, the desirable SD&FA method applied to thin-haul operations needs to capture departure time preferences of passengers traveling by ground transport to perform SD&FA with flexibility, without significant penalties in the fidelity level, and with reduced computational time. Based on these requirements, it is possible to define the criteria that the adopted methodology must meet to answer **RQ2**:

Criteria RQ2: input needed to perform schedule design, flexibility, fidelity level, and computational time.

As the methodologies defined by Alternatives 1 to 3 may not be able to fulfill the requirements to answer **RQ2**, the research gap can be addressed if the ITD-FA method represented by Alternative 3 is adapted to capture the *hourly trip distribution* of the alternative modes of transport competing with air service. In other words, the SD&FA model applied to thin-haul operations requires as input the hourly frequency of intercity trips covered using ground transportation. This frequency defines how many passengers wish to travel a certain route at an specific departure time. With that, the attractiveness of each itinerary can be defined based on the other itinerary attributes only. By multiplying both frequency and itinerary attractiveness, it is possible to determine how many passengers are willing to travel at an specific itinerary and departure time. In this case, the frequency can be easily replaced depending on the hourly trip distribution being considered. In addition, the demand at the itinerary level should be *fixed* to limit the number of passengers transported at each itinerary, instead of allowing this number to be proportional to the itinerary attractiveness. In this way, passengers cannot freely switch between itineraries. This approach also allows a reduction in the number of design variables, since itineraries with lower demand can be disregarded in advance. It represents the proposed methodology, defined by **Alternative 4**.

Therefore, the current methodologies and the proposed approach can be summarized as follows:

Alternative 1: basic fleet assignment model (FAM) allowing flexible departure time as proposed by Rexing et al. [41] and Desaulniers et al. [42].

- *Pros:* Traditional approach that is commonly adopted and well proven in the literature;
- *Cons:* Needs baseline schedule as input, low fidelity due to leg-based approach, computationally expensive.

Alternative 2: integrated schedule design and itinerary-based fleet assignment model (ISD-FA), proposed by Lohatepanont et al. [44].

- *Pros:* Medium fidelity, itinerary-based approach considering network effects;
- *Cons:* Requires baseline schedule as input, fixed recapture rate, computationally expensive.

Alternative 3: integrated timetable development and fleet assignment model (ITD-FA) proposed by Wei et al. [47], that adopts the attractiveness approach proposed by Wang et al. [33] and the utility values developed by Lurkin et al. [31].

- *Pros:* High fidelity, itinerary-based approach considering network effects, no baseline schedule needed;
- *Cons:* Requires refined data for departure time preference, computationally expensive, low flexibility.

Alternative 4: adapted ITD-FA model, that captures hourly trip distribution from alternative modes of transport without coupling it to the itinerary attributes, and restricts passengers to switch itineraries.

- *Pros:* Medium fidelity, itinerary-based, captures competition with other modes of transportation, higher flexibility, reduced computational time;
- *Cons:* Does not account for all network effects (recapture).

The proposed new approach represented by Alternative 4 is expected to successfully tackle the research gap while best meeting the criteria. This claim can be formulated as the following hypothesis:

HP2: Current ITD-FA models can be adapted to support thin-haul scheduling decisions *if* the relationship between hourly demand distribution and flight schedule is captured considering the competition with alternative modes of transport.

HP2 can be substantiated by evaluating each one of the alternatives considering the established criteria and verifying that the proposed approach is the most efficient. However, clearly alternatives 1, 2, and 3 cannot be tested, since these options require input data not available for thin-haul operations. Therefore, testing **HP2** consists of demonstrating that SD&FA can be successfully performed using an hourly distribution and any notional value of attractiveness, with the parameters that drive the scheduling decisions decoupled from the itinerary attributes. Therefore, the following experiment is proposed:

- For a complete set of routes, with notional demand considering a fixed mode split across all routes and the same attractiveness for the potential itineraries of any market:

    1. Perform the adapted ITD-FA method considering the hourly passenger flow from ground transportation trips and verify that the model outputs a feasible schedule and the required metrics of effectiveness, including profit, passengers transported, and percentage of demand and routes served.

The experiment is expected to increase the confidence in **HP2** by demonstrating that the SD&FA using the cold start approach can be successfully performed considering the hourly demand distribution. The method proposed in **HP2** should be able to output the metrics of effectiveness, defined mainly by the operating profit and the total demand served, and to demonstrate the schedule design is impacted by the hourly trip distribution.

2.3 Thin-Haul Concept of Operations

RQ3: *How can the concept of operations to effectively serve the thin-haul market be determined?*

2.3.1 Literature Review

Historically, short-range routes have been served by commuter airlines operating propeller-driven aircraft under hub-and-spoke networks [2, 4]. In the traditional concept of operations (CONOPs) of these carriers, the majority of flights are offered from smaller airports to large hubs, using a fleet composed by aircraft ranging from 9 to 60 seats [3]. Nonetheless, when passenger choice is considered and travel time has a major role in this choice, it is not clear how effective the traditional concept of operations adopted by commuter airlines can be.

The network structure is one of the main operations decisions impacted when passenger choice is considered due to the trade-off between increasing profitability and reducing travel time. Hub-and-spoke systems are widely adopted by airlines since it presents higher profit and load factor due to the increased traffic volume at hubs. For short-range routes with low passenger volume, adopting a hub-and-spoke structure could facilitate profitable operations. Nonetheless, this network structure is composed of circuitous routes, forcing passengers to spend more time waiting and flying multiple legs. The routes offered become unattractive time-wise, which may limit the odds of air service expansion in the thin-haul market. Besides, it may not improve the door-to-door travel time of passengers, which is one of the main aspirations behind revitalizing thin-haul operations. Point-to-point flights, on the other hand, allow faster commute between cities and therefore are more attractive to passengers. The challenge lies on airlines being able to maintain profitable operations over low-volume routes with a pure point-to-point network. A hybrid network containing both non-stop and connecting flights, on the other hand, could potentially increase the odds of successful air service, capable of capturing more passengers and serve more routes while keeping high levels of profit and favorable time savings.

The hub location may also present a major impact on the operations effectiveness by dictating the possible connections in the network. This can affect the routes that can be potential served and ultimately the travel time of those routes connecting airports too far from the hub. Other operations decisions, such as the fleet composition and the performance attributes of the chosen aircraft, can also influence the potential flights in the network, thus impacting the airline profit and the door-to-door travel time of passengers.

Despite the potential influences of operations decisions, there have not been many studies analyzing thin-haul operations considering different CONOPs. The few studies that simulated operations focused on the SATS program [14–16] and did not investigate different operational scenarios. Oliveira et al. [48] recently compared different CONOPs for thin-haul operations using an allocation problem. The authors investigated commuter operations under different network structures and technological assumptions for the aircraft employed in the fleet. The results suggested that point-to-point flights can be integrated to the typical hub-and-spoke network adopted by commuter airlines. The authors also demonstrated the potential that electric aircraft have to reduce operating cost and increase airline profitability as the technological levels improve in future years. However, allocation problems do not capture the schedule element, in which case the connection opportunities are not evaluated and the results might be inconclusive. The authors also did not consider the value passengers place on time savings, which can also lead to inaccurate observations.

Identifying the most efficient operations decisions to serve the thin-haul market under passenger behavior considerations could be the key to successfully promote thin-haul operations. Nonetheless, a thorough search of the relevant literature did not reveal which concept of operations would be more effective to serve the thin-haul market when the objective is to balance airline profitability, air service expansion, and passenger time savings. This leads to the third research gap:

Gap RQ3: There is no current study identifying the concept of operations to effectively serve the thin-haul market when the objective is to increase airline profitability while expanding the air service within small communities and reducing the door-to-door travel time of passengers.

2.3.2 Overarching Hypothesis and Framework Demonstration

RQ3 can be addressed if a *comprehensive assessment* of the thin-haul market is performed by integrating passenger demand estimation with operations analysis to determine the true market share and the profitable routes. This is equivalent to combining the approaches endorsed by **HP1** and **HP2** within a framework that must allow different operational scenarios to be evaluated. Once substantiated, **HP1** and **HP2** combined lead to the proposed methodology on this thesis, which integrates the SD&FA model adapted to thin-haul operations with demand assessment accounting for passenger choice. This can be stated as the following *overarching hypothesis*:

Overarching Hypothesis A comprehensive assessment of the economic viability of thin-haul scheduled operations needs to integrate thin-haul demand estimation methods with SD&FA techniques to account for the true market share and multiple concepts of operations considering the competition with alternative modes of transport.

The framework can then be used to analyze different operational scenarios and determine the most efficient CONOPs. Therefore, a demonstration is proposed to illustrate the capabilities of the framework and to indicate that the proposed methodology can successfully analyze thin-haul operations decisions under passenger choice considerations.

A series of case studies are proposed for this demonstration to illustrate some of the potential scenarios that can be tested and analyzed using the framework:

- **Network structure:** analyze three different network structures, namely pure point-to-point, hub-and-spoke, and hybrid network composed of non-stop and connecting flights. Compare the metrics of effectiveness of these options to determine the most efficient network structure for thin-haul operations;

- **Aircraft performance characteristics:** analyze the impact of different aircraft performance attributes in the metrics of effectiveness;

- **Hub location:** analyze the impact of the hub location in the effectiveness of thin-haul operations.

This demonstration is expected to prove that the proposed methodology can provide a comprehensive assessment of thin-haul operations under different circumstances. This means that the framework is able to successfully output the metrics of effectiveness necessary for this complete analysis, which includes the true market share and thin-haul routes that can be profitably served. A thorough search in the literature revealed that this comprehensive assessment of thin-haul operations has not yet been accomplished. Therefore, the proposed methodology is more suitable to analyze thin-haul operations under multiple scenarios.

2.4 Thesis Structure

Figure 2.2 summarizes the thesis structure, with the relationship between the research questions, hypothesis, and experiments derived to build the proposed methodology.

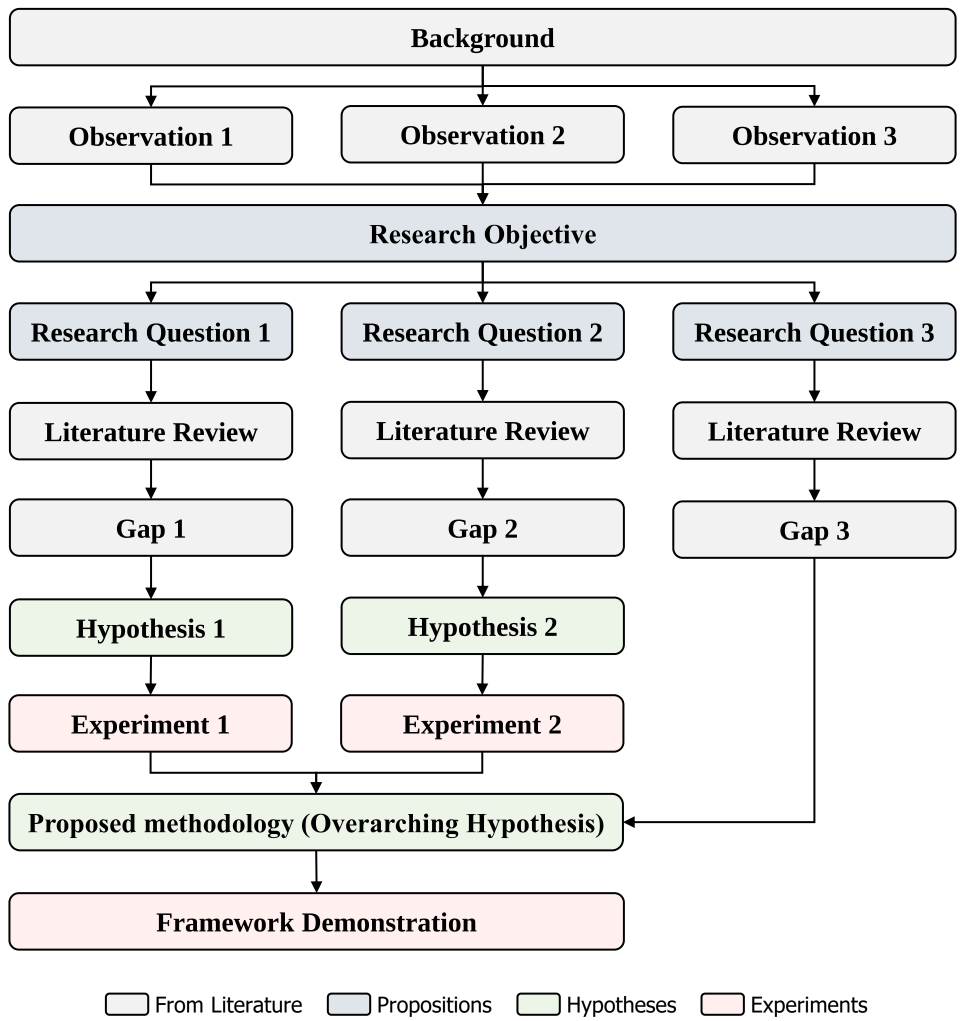


Figure 2.2: Thesis structure

CHAPTER 3
FRAMEWORK DEVELOPMENT

The decision-making framework was developed in two main phases: passenger demand analysis and thin-haul ISD-FA optimization. The first stage was divided in two sub-steps: assessment of potential routes and their daily demand, and computation of potential market share and itinerary attractiveness. This last step was performed considering the itinerary definition that depends on the network structure and the potential departure times. The second stage of the framework performs the concurrent schedule design and fleet assignment, according to the defined itineraries, the demand results from the passenger demand analysis, fleet composition data, and the hourly trip distribution. The last element defines the frequency of trips for each potential departure time.

The methodology outputs the metrics of effectiveness necessary to evaluate the feasibility of thin-haul operations, which are the operating profit, true market share, number of passengers transported, average time saved, and number of routes and airports served. Figure 3.1 depicts the framework structure and the relationship between the stages. The passenger demand analysis and the ITD-FA methodology applied to thin-haul operations are described in the following sub-sections.

3.1 Terminology

For the scope of this thesis, the following terminology is considered:

- *Route or O&D pair:* a one-way trip from an origin city to a destination city, associated to an unidirectional demand;
- *Leg or flight leg:* an airport-to-airport segment in which the airline operates non-stop flights;

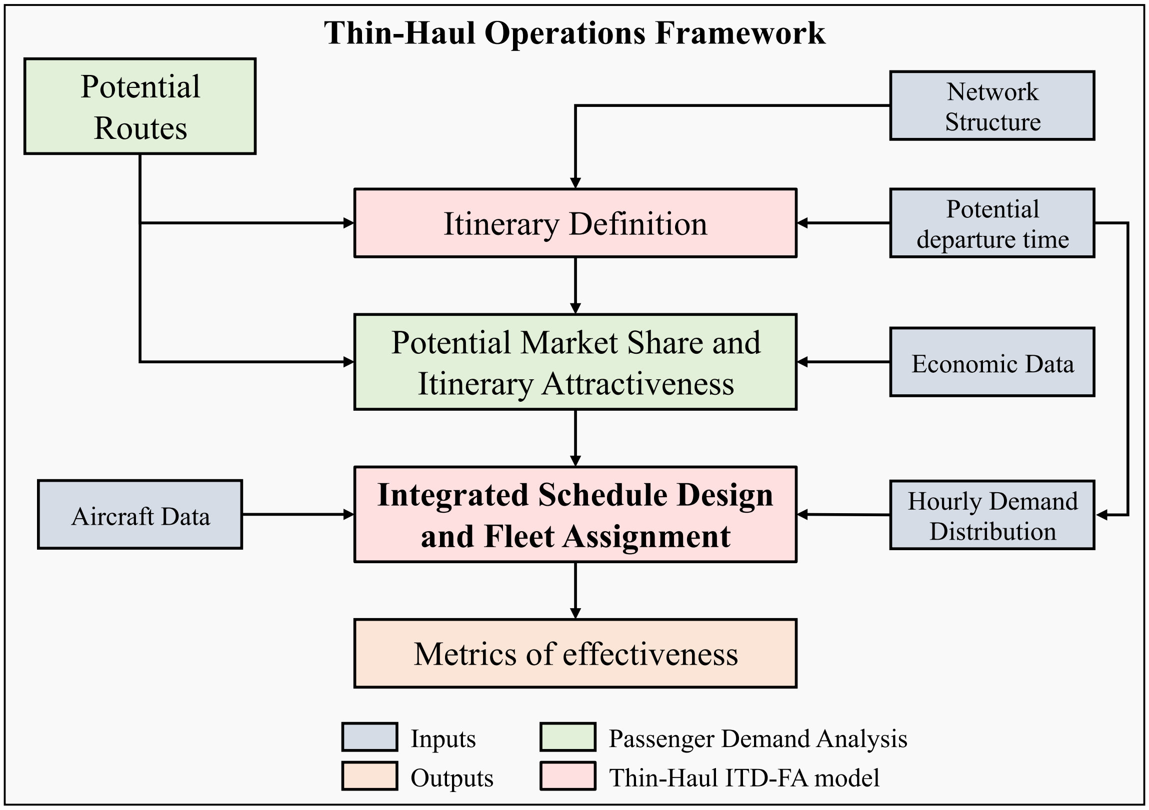


Figure 3.1: Methodology Overview

– *Flight:* an operation in a flight leg at a specific departure time;

– *Itinerary or path:* a sequence of flight legs used by passengers to complete a trip, going from an origin to a destination city. An itinerary may have one or multiple flight legs, and a route may present multiple itineraries;

– *Aircraft type:* an aircraft model with known characteristics, including seat capacity, range, and turnaround time, that are shared by all aircraft of the same type.

3.2 Thin-haul Passenger Demand

Similarly to the proposed approaches described in section 2.1, passenger demand for thin-haul scheduled operations is determined by adapting the FSM steps. First, trip distribution and trip generation are performed to define the potential routes, i.e., those routes currently served by ground transport that could be potentially served by an airline. Subsequently, mode split is determined for each route along with the attractiveness of the available itineraries.

3.2.1 Potential Thin-haul Routes

To determine the potential thin-haul routes, three main databases are required as input: one containing county (or equivalent) information, another providing airport data, and a third one with county-to-county passenger travel data for different modes of transport. The county database needs to specify the location of each county, identified by centroid latitude and longitude, and the region (or equivalent) to which the county belongs. Similarly, the airport database must contain information about the facility location, i.e., latitude, longitude, runway length, and the county in which the airport is located. Lastly, the passenger travel database needs to provide the number of county-to-county trips done using different modes of transport.

The set of potential routes is determined integrating these three databases. First, the counties in a selected region are crossed among each other to create potential origin and destination (O&D) pairs in the county-to-county level. Subsequently, the number of trips related to the O&D pairs are obtained from the passenger travel database, for each mode of transport, creating a full set of routes for a certain region. It is important to notice that demand in this case is *unidirectional*. The airport database, on the other hand, is filtered based on the runway length and the airport type. Following that, each county is associated to an airport, assigned based on the facility location. The O&D pair is now defined as an origin airport to a destination airport, i.e., in the airport-to-airport level. If there is no airport located in the county, the closest airport within a defined distance radius is assigned to the county. If no airport was associated to a particular county, i.e., there is no airport nearby, the O&D pairs containing that county are removed. On the other hand, in case there are airports serving multiple counties resulting in O&D pairs appearing more than once in the dataset, the routes are combined, the demand added, and the county in which the airport is located is taken as the reference county. Figure 3.2 shows an example of this potential combination. Airport A is located at county 3, but it is also assigned to counties 1 and 2. Similarly, airport B is located at county 6, but it is associated to counties 4 and 5 as well. In this case, the demand of route A-B would be determined by merging the nine county-to-county possible combinations with 1, 2, and 3 as the origin counties and 4, 5, and 6 as the destination counties, and counties 3 and 6 would be the airport reference ones. Reference counties are adopted to further determined the driving distance of an O&D pair.

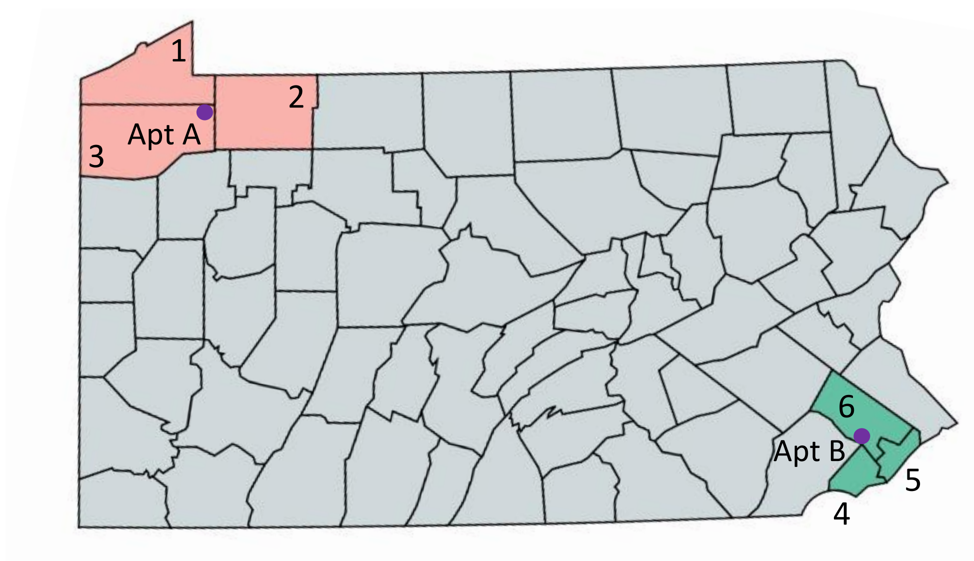


Figure 3.2: Example of O&D pairs merged

The routes that could be potentially served by thin-haul operations are determined once the full set is filtered considering the daily demand levels and the range of flight length, assumed to be equivalent to the great circle distance. After that, the road distance between the county centroids in an O&D pair and between airport and reference county are computed using any geospatial or highway library available. The result is a database with potential routes, daily demand for each mode of transport, and road distances for a selected region, that can be further used to determine the potential market share. Figure 3.3 depicts the step-by-step process to identify the potential thin-haul routes.

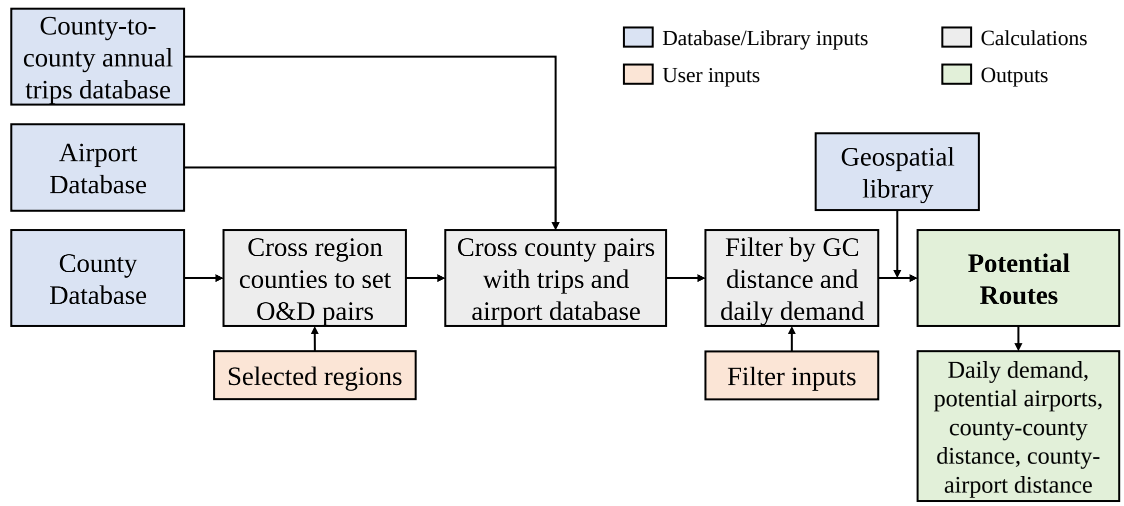


Figure 3.3: Methodology to determine potential thin-haul routes

3.2.2 Potential Market Share and Itinerary Attractiveness

The outputs from the previous section provide the daily demand of an alternative mode of transport for a set of O&D pairs. Nonetheless, not all passengers are expected to choose air service over ground transport in case operations are established. At the same time, for each route and each departure time, passengers are likely to have different itinerary options available. Therefore, the potential demand for each O&D pair needs to account for mode and itinerary choice.

Consider a set of itineraries of an O&D pair at a departure time t, each one with different values of ticket price, number of connections, and trip time. When compared to the alternative mode of transport considered in the analysis, one itinerary will be more attractive to passengers than the others. The attractiveness of each itinerary defines which paths, if any, travelers will prefer if they switch from ground transport to thin-haul air service.

Previous studies demonstrated the relevance of time savings and cost difference in passengers decisions when choosing between thin-haul air service and alternative modes of transport, as well socioeconomic factors. Therefore, these factors are considered when defining attractiveness among a set of itineraries and the ground transport alternative. In this case, itinerary attractiveness and mode split are computed simultaneously. The *attractiveness* of an itinerary or path p is computed based on the cost difference ($\Delta Cost$) and the time difference ($\Delta Time$) between flying through the itinerary or using an alternative mode of transport. The ratio between these two metrics is the *opportunity cost*, expressed by $\Delta Cost/\Delta Time$ in Equation 3.1, and represents how much more the passenger would have to pay to experience one hour of time savings.

$$\left(\frac{\Delta Cost}{\Delta Time}\right)_p = \frac{Cost_p - Cost_{alt}}{Time_{alt} - Time_p} \tag{3.1}$$

where $Time_p$ is the total time when flying path p, $Cost_p$ is the total cost to fly itinerary p including the ticket price, and $Cost_{alt}$ and $Time_{alt}$ are the cost and trip time to cover the same O&D pair using an alternative mode of transport.

The decision between flying a specific itinerary or choosing the conventional ground transport depends on the value travelers place in their time saved. This value of travel time savings (VTTS), or cost of time savings, is generally related to the income levels of passengers and the trip purpose [27, 29, 49]. Therefore, if the *income distribution* of travelers is known, the passengers that would be willing to switch from ground transport to any itinerary can be determined. For instance, consider the set P' of three itineraries p_1, p_2, and p_3 departing at time t, and assume that $\Delta Cost/\Delta Time$ is greater for itinerary p_3, p_2, and p_1, respectively, i.e, $(\Delta Cost/\Delta Time)_3 > (\Delta Cost/\Delta Time)_2 > (\Delta Cost/\Delta Time)_1$. Figure 3.4 shows an example of how the switching percentage can be computed. Any passenger who earns more than $(\Delta Cost/\Delta Time)_{p_3}$ can afford to switch to air service and choose anyone of the three available itineraries. Passengers with hourly earnings between $(\Delta Cost/\Delta Time)_{p_2}$ and $(\Delta Cost/\Delta Time)_{p_3}$ can afford itineraries p_1 and p_2, while travelers with wages between $(\Delta Cost/\Delta Time)_{p_1}$ and $(\Delta Cost/\Delta Time)_{p_2}$ can only afford to choose itinerary p_1. Any passenger earning less than $(\Delta Cost/\Delta Time)_{p_1}$ can only travel using the conventional ground transport.

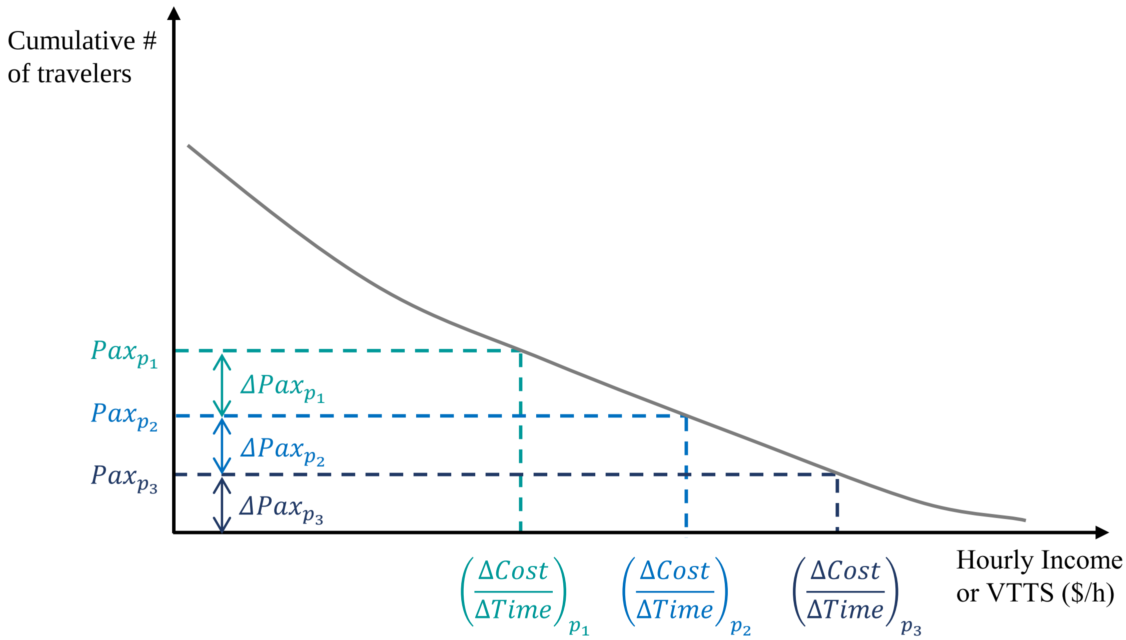


Figure 3.4: Determining switching percentage based on income distribution

Therefore, the switching percentage for each itinerary in the set is given by Equation 3.2, where ΔPax_p is defined according to Figure 3.4. In this context, the overall percentage of passengers that would switch from ground transport to thin-haul air service at a certain departure time will be the sum of all switching percentages in the set of itineraries.

$$Perc_p = \frac{\Delta Pax_p}{Total\ number\ of\ travelers} \tag{3.2}$$

Nonetheless, as aforementioned, in some occasions passengers can afford more than one available itinerary. In this case, travelers tend to prefer paths with greater time savings benefits. For each itinerary p_i, with opportunity cost represented by $(\Delta Cost/\Delta Time)_i$, the *sub-attractiveness* $(at_{p_{i-j}})$ is then defined with respect to time savings among the itineraries that the passenger can afford, represented by p_j. This subset of itineraries is denoted by P_i'. For instance, passengers able to afford itinerary p_3 can also pay for paths p_1 and p_2, in which case, for itinerary p_3, the subset P_3' is composed by paths p_1, p_2, and p_3, as exemplified in Figure 3.5. Equation 3.3 demonstrates how the sub-attractiveness can be calculated.

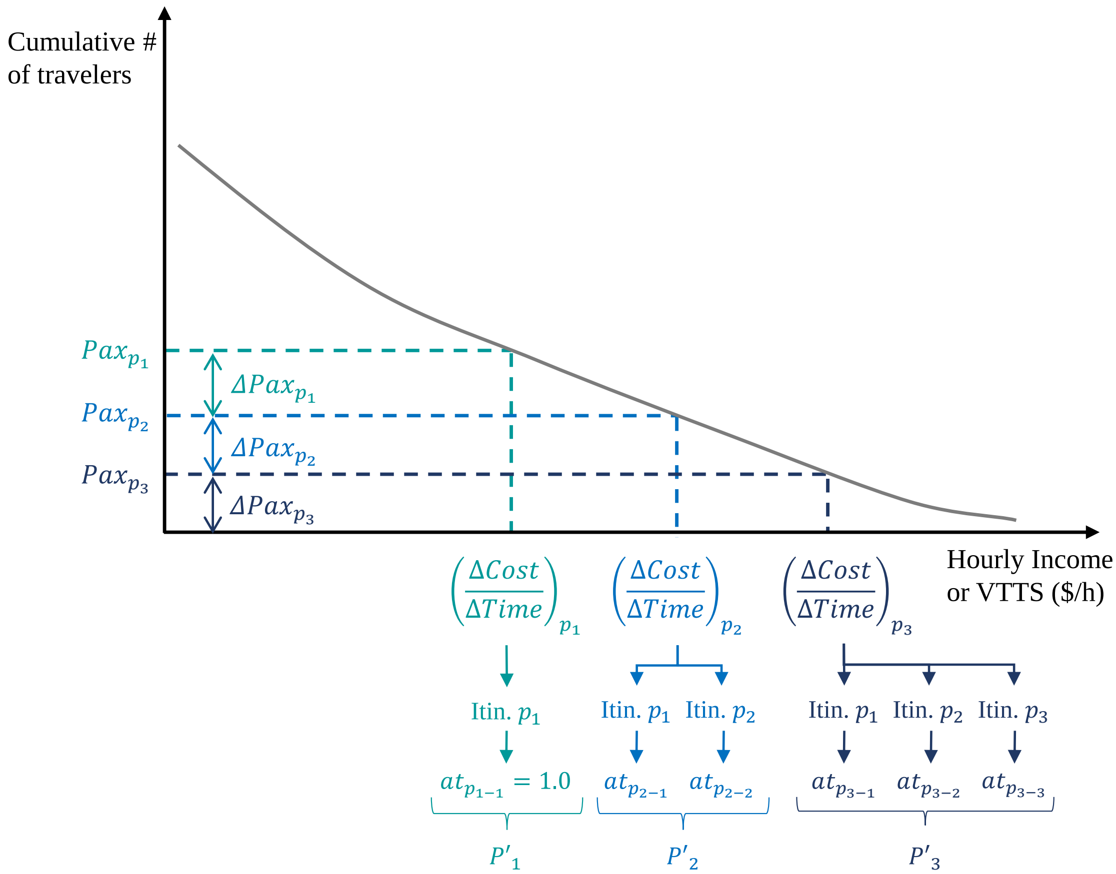


Figure 3.5: Sub-attractiveness example

$$at_{p_{i-j}} = \frac{\Delta Time_{p_j}}{\sum \Delta Time_{p_j}}, \qquad \forall p_j \in P'_i \tag{3.3}$$

where $\Delta Time_{p_j}$ represents the time savings of itinerary p_j and $at_{p_{i-j}}$ equal zero if p_j is not part of the subset P'_i. The overall *attractiveness factor* At_p of any itinerary p can then be computed by combining the switching percentages with the sub-attractiveness, as shown in Equation 3.4

$$At_p = At_{p_j} = \sum Perc_i \cdot at_{p_{i-j}} \tag{3.4}$$

For the example depicted in Figure 3.5, Equation 3.4 can be decomposed into the following expressions:

$$At_{p_1} = Perc_1 \times at_{p_{1-1}} + Perc_2 \times at_{p_{2-1}} + Perc_3 \times at_{p_{3-1}}$$
$$At_{p_2} = Perc_2 \times at_{p_{2-2}} + Perc_3 \times at_{p_{3-2}}$$
$$At_{p_3} = Perc_3 \times at_{p_{3-3}}$$

The only exception for Equation 3.4 is when a non-stop itinerary presents the lower values of $(\Delta Cost/\Delta Time)$ and the higher values of time savings. Considering the higher preference passengers often have towards non-stop paths [31], the attractiveness of this itinerary is set to be the total switching percentage and the attractiveness of the others itineraries are set to be zero. In other words, in this scenario all passengers will choose to flight the non-stop itinerary if they can afford it.

As previously mentioned, this methodology is valid for one-to-one comparison, i.e., when comparing thin-haul operations with one mode of ground transportation. If multiple modes are considered, this step-by-step process needs to be repeated for each one of them. The final number of passengers for each itinerary will then be the combination of results for each mode considered.

3.3 Thin-haul Operations ISD-FA Model

3.3.1 Time-Space Network

The flight network is constructed using the *time-space representation* proposed by Hane et al. [40] and assuming that the schedule repeats *daily*. This type of representation uses *nodes* and *arcs* to describe aircraft position and movements throughout the entire network. Each airport is depicted as a vertical timeline with *nodes* representing a time instant *t*. The first node from top to bottom defines the starting time of the operation day. All nodes represent the time of departures or arrivals that occur throughout the day. Each flight in the network is represented by a *flight arc*, that covers a flight leg f from an origin airport to a destination airport departing at time *t*. A flight arc starts at a departure node and ends at an arrival node. The latter is given by the schedule arrival time plus the aircraft turnaround time, i.e., when the aircraft is ready to fly again. *Ground arcs* link one node to another in the same airport, defining the period the aircraft remains grounded. At last, *overnight arcs* are constructed in the network to link the end of the day to the beginning of the day in an airport when the schedule is daily, representing aircraft that stayed overnight in the airport.

Figure 3.6 shows a typical time-space network and its main elements. In this representation, the number of aircraft of each type can be found by summing the flow of all ground and flights arcs at a certain count time. A time-space network is created for each aircraft type to represent the aircraft position throughout the entire network during a day of operation.

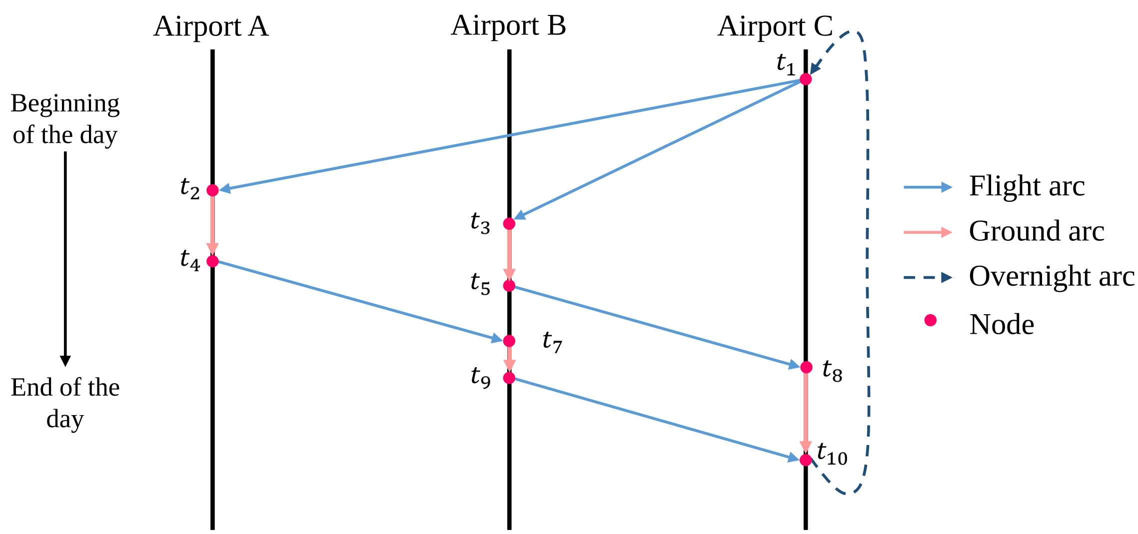


Figure 3.6: Time-space network representation

3.3.2 Time Window Discretization and Hourly Demand Distribution

The integrated schedule design and fleet assignment for thin-haul operations is performed without a baseline schedule. To achieve that, the full day of operations is divided in discrete time windows, similarly to the approach proposed by Wei et al. [47]. The time periods must be small enough so the assumption that no more than one flight occurs in that time period is valid. Time windows are enclosed by two nodes, so each airport in the network will have $n + 1$ nodes for n discrete periods, as shown in Figure 3.7. These nodes represent a time instant *t* that can either be a departure or an arrival time. Flight arcs are created with departure node at the beginning of each time window. The arrival time is given by the flight time plus the aircraft turnaround time, and its node is represented by the end node of the time period in which the flight arc arrives. For instance, in Figure 3.7 the flight arc departs at node t_4 and arrives between nodes t_6 and t_7, in which case the arrival node is represented by node t_7. The exception for this representation occurs when the flight arrives after the node that represents the end of operations in the day, t_{end}. In this case, the flight arrival is denoted by the node t_{end}. It is important to note that, since departures are assigned only to the node at the beginning of each time window, no flight departs at the end node t_{end} from any airport.

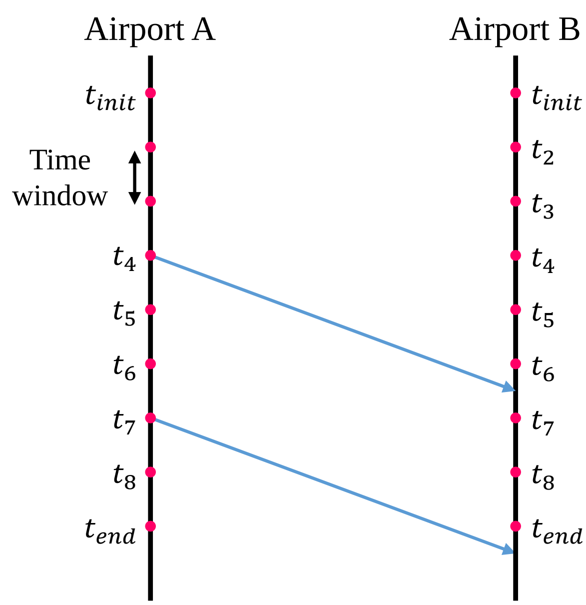


Figure 3.7: Time-window discretization

Therefore, the time-window discretization dictates possible flight departure times, and consequently the potential flight connections in the network depending on the network structure selected. If the network has a mix of non-stop and connecting flights, it will result in different available itineraries for the same departure time. To determine the *frequency* of passengers wishing to travel at each one of these potential departure times ($freq_t$), the discretization is linked to the *hourly demand distribution*, as shown in Figure 3.8. The hourly distribution is based on how trips covered using alternative modes of transport are allocated throughout the day. In this case, it is expected that passengers willing to switch to air service will travel in similar hours of the day. For every route, each departure at time *t* will be associated to a number of passengers that wish to fly at that time, according to the demand distribution.

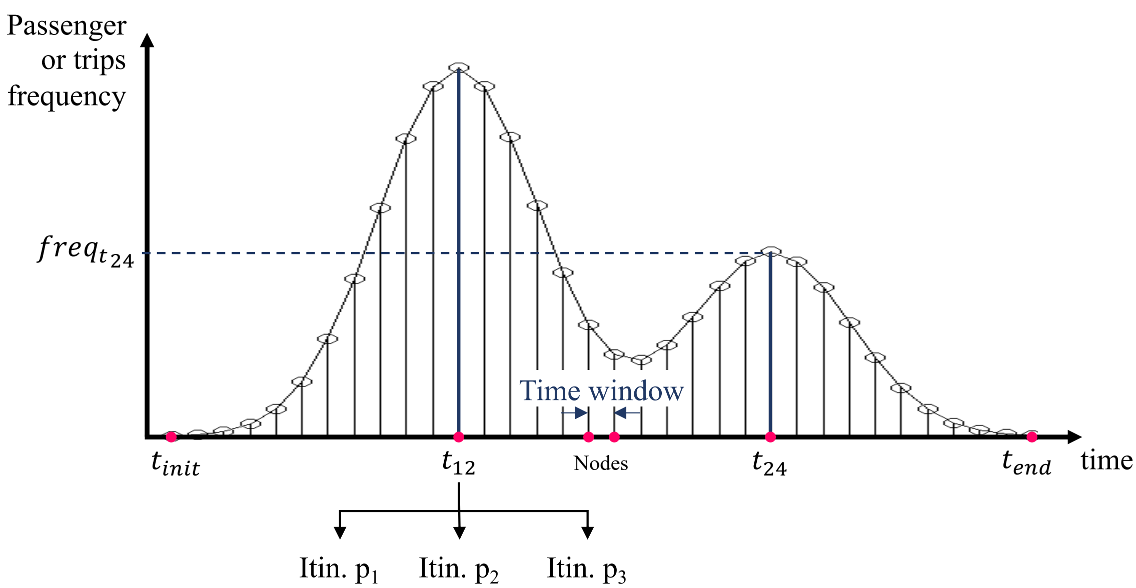


Figure 3.8: Match between hourly trips distribution and time-window discretization

Note that passenger demand at each departure node t is associated to an itinerary set, and not to a flight arc. One flight arc may be part of many different itineraries and therefore transport passengers coming from different O&D pairs and different itineraries.

Therefore, with the frequency of trips at the itinerary departure time t ($freq_t$), the daily demand of the O&D pair (Dem_{OD}) and attractiveness of the itinerary p (At_p) determined in subsection 3.2.2, the passenger demand of the itinerary (Dem_p) is then defined by Equation 3.5. Note that $freq_t$ can be easily replaced by any distribution pattern adopted, granting flexibility to the methodology.

$$Dem_p = Dem_{O\&D} \times freq_t \times At_p, \quad \forall p \in O\&D \tag{3.5}$$

3.3.3 Mathematical Formulation

The adapted ITD-FA model is formulated as a *Mixed Integer Linear Programming (MILP)* problem. By adopting the time-space network and dividing the day of operations in discrete time periods, the optimization problem can be written as follows:

Sets and indices:

S - set of airports, or stations, in the network, indexed by s;

K - set of aircraft types, indexed by k;

T - set of time instants in the day, indexed by t;

N - set of nodes in the network, representing an aircraft type k at station s at time t, indexed by (s, k, t);

F - set of all flight legs between two airports in the network indexed by f. In this case, a flight with departure time at t is represented by (f, t);

$O(s) \subset F$ - subset of flight legs that departs from airport s;

$I(s) \subset F$ - subset of flight legs that arrives at airport s;

P - set of itineraries indexed by p;

Input parameters:

$DOC_{f,t,k}$ - cost of operating aircraft type k on flight leg f departing at time t;

$dist_f$ - distance of flight leg f;

Rw_s - runway length of airport s;

$Fare_p$ - fare of itinerary p;

Dem_p - demand of itinerary p, as defined in subsection 3.3.2;

Cap_k - capacity of aircraft type k;

$Range_k$ - design range of aircraft type k;

$TOFL_k$ - takeoff field length of aircraft type k;

UP_k - daily unit price paid by the airline to lease one aircraft of type k;

t_i, t_e - first and last time instant of the day;

$D_{(f,t)}$ - scheduled departure time of a flight operating on leg f with arrival node at time t;

$$\delta^p_{f,t} = \begin{cases} 1, & \text{if flight } (f,t) \text{ is part of itinerary p} \\ 0, & \text{otherwise} \end{cases}$$

Design Variables:

$$x_{f,t,k} = \begin{cases} 1, & \text{if aircraft } k \text{ is assigned to flight } (f,t) \text{ for } t \neq t_e \\ 0, & \text{otherwise} \end{cases}$$

Pax_p - number of passengers travelling on itinerary p;

y_{s,k,t_e,t_i} - number of aircraft type k grounded at airport s between time t_e and t_i. Represents the overnight arc of airport s;

y_{s,k,t,t^+} - number of aircraft type k grounded at airport s between two adjacent nodes at instants t and t^+. For a time right after t_i, this variable is represented by y_{s,k,t_i,t^+}.

$y_{s,k,t^-,t}$ - number of aircraft type k grounded at airport s between two adjacent nodes at instants t^- and t. For a time right before t_e, this variable is represented by y_{s,k,t^-,t_e}.

$to\, maximize:$

$$\sum_{p\epsilon P}(Fare_p \cdot Pax_p) - \sum_{f\epsilon F}\sum_{t\epsilon T}\sum_{k\epsilon K}(DOC_{f,t,k} \cdot x_{f,t,k}) - \sum_{s\epsilon S}\sum_{k\epsilon K}(UP_k \cdot y_{s,k,t_e,t_i}) \quad (3.6)$$

$subject\, to:$

$$\sum_{k\epsilon K} x_{f,t,k} \leq 1, \quad \forall\, f \in F, \quad \forall t \in T \quad (3.7)$$

$$y_{s,k,t^-,t} + \sum_{f\epsilon I(s)} x_{f,D(f,t),k} - y_{s,k,t,t^+} - \sum_{f\epsilon O(s)} x_{f,t,k} = 0, \quad \forall (s,k,t) \in N,\ t \neq t_i, t_e \quad (3.8)$$

$$
\begin{aligned}
y_{s,k,t_e,t_i} &= y_{s,k,t_i,t^+} + \sum_{f \epsilon O(s)} x_{f,t_i,k}, \quad \forall (s,k,t_i) \in N \\
y_{s,k,t^-,t_e} + \sum_{f \epsilon I(s)} x_{f,D(t_e),k} &= y_{s,k,t_e,t_i}, \quad \forall (s,k,t_e) \in N
\end{aligned} \tag{3.9}
$$

$$
\sum_{p \epsilon P} Pax_p \delta^p_{f,t} \leq \sum_{k \epsilon K} x_{f,t,k} \cdot Cap_k, \quad \forall f \in F, \quad \forall t \in T \tag{3.10}
$$

$$
Pax_p \leq Dem_p, \quad \forall p \in P \tag{3.11}
$$

$$
x_{f,t,k} \cdot dist_f \leq Range_k, \quad \forall f \in F, \quad \forall t \in T, \ \forall k \in K \tag{3.12}
$$

$$
x_{f,t,k} \cdot TOFL_k \leq Rw_s, \quad \forall f \in O(s) \cup I(s), \ \forall t \in T, \ \forall k \in K, \ \forall s \in S \tag{3.13}
$$

$$
Pax_p \geq 0, \quad y_{s,k,t,t^+} \geq 0, \quad y_{s,k,t^-,t} \geq 0, \quad \forall p \in P, \ \forall s \in S, \ \forall k \in K, \ \forall t \in T \tag{3.14}
$$

Equation 3.6 is the objective function of the optimization problem representing the profit, that is set to be maximized. The first term is the revenue generated by the passengers captured by the airline, and the second term is the total cost of operating the assigned aircraft in the flight legs. The third term represents a *penalty function* based on the unit price per day for each aircraft that is added to the network to cover the flights. The unit price represents the daily amount an airline needs to pay to lease a certain aircraft type, and is computed based on the aircraft acquisition, depreciation, and loan costs. This penalty function is embedded in the objective function to hinder the optimizer from including an unconstrained quantity of aircraft, since there is no limit for the fleet size. In this case, it is possible to evaluate the total number of aircraft that will maximize the profit considering the daily aircraft unit price the airline would need to afford to maintain its operations. Since no flight is allowed to depart or arrive between times t_e and t_i, the total number of aircraft type k can be determined by adding the number of aircraft grounded in the overnight arcs y_{s,k,t_e,t_i} in all airports.

Equation 3.7 is the set of cover constraints that in this case defines if a flight leg can or cannot be flown by an aircraft. This aligns with the goal of investigating which routes can be profitably served, without requiring that all potential routes must be covered. Equation 3.8 is the set of balance constraints, that ensures aircraft flow conservation at each node. Equation 3.9 is the same set of balance constraints, but adapted to the last and first node of each station to ensure that the schedule is daily and repeats in the following day. Equation 3.10 represents the capacity constraints, which guarantee that the total number of passengers transported in each leg cannot exceed the capacity of the aircraft assigned for that leg. Equation 3.11 defines that the number of passengers transported in a given itinerary cannot exceed its demand. This constraint also prevents passengers from switching to itineraries they might not be able to afford. Besides, as aforementioned, the definition of Dem_p according to Equation 3.5 allows the adoption of any distribution, granting flexibility to the methodology. Equation 3.12 and Equation 3.13 define that an aircraft can be assigned to a flight only if its range is enough to cover the flight leg and if the aircraft can takeoff and land in both airports. At last, Equation 3.14 represents the numeric constraints of the design variables.

Additional *operational constraints* can be incorporated to the formulation as needed. These constraints, formulated as follows, are related to the fleet size and minimum flight distance:

Additional parameters:

AC_k - total number of available aircraft type k in the fleet;

d_{min} - minimum flight distance that is allowed to be covered by any aircraft type;

$$\sum_{s \epsilon S} y_{s,k,t_e,t_i} \leq AC_k, \qquad \forall k \in K \tag{3.15}$$

$$x_{f,t,k} \cdot dist_f \geq d_{min}, \quad \forall f \in F,\ \forall t \in T,\ \forall k \in K \tag{3.16}$$

Equation 3.15 limits the total number of aircraft of each type by the fleet size, while Equation 3.16 dictates that flights with less than the minimum flight distance cannot be covered.

3.4 Framework Implementation

The framework is implemented on a *python-based* environment. The details of the complete implementation are described in the following sub-sections.

3.4.1 Potential Routes Results

The county database was retrieved from the US Census Bureau [50], which provides the latitude, longitude, and region location of every county in the USA. The counties are grouped in nine regions: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain Division, and Pacific Division. Due to its high population density, the regions selected are the New England and Mid-Atlantic in the Northeast USA, composed of the following states: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York and Pennsylvania. The group of states contain 217 counties, resulting in 46,872 county-to-county pairs.

The next database adopted was the *Airport Data and Contact Information* from the Federal Aviation Administration (FAA) [8], which contains detailed information of all airports in the USA, including location, runway length, classification, and number of operations per year. The database was initially filtered considering public airports with runway length greater than 3,000 ft, which is the typical takeoff field length of the 9-seat aircraft category. Subsequently, to remove clusters present in some areas, if two airports are located within a 15-mile great circle (GC) distance radius, the airport with *lower* level of operations was kept, with the exception of some strategic airports such as Albany, Boston, and Buffalo Niagara airports. The outcome is a set of 170 airports in the studied region. As described in subsection 3.2.1, the county database was combined with the airport database. Counties with no airport were assigned to the closes airport considering a GC distance radius of 20 miles, similarly to previous studies [14].

Finally, the dataset of potential pairs was combined to the county-to-county annual passenger flow dataset retrieved from the *Traveler Analysis Framework* developed by the Federal Highway Administration [51]. The database estimates annual passenger travel for trips greater than 100 miles by five modes of transport: air, rail, bus, automobiles business, and automobile leisure. This was accomplished by combining previous surveys conducted by the American Travel Survey (ATS) and the National Household Travel Survey (NHTS), as well as data from FAA and Amtrak. The result was a set of trip tables with county-to-county one-way passenger flow information. More than 75% of the trips were less than 300 miles with and average distance of 297.7 miles, which it is consistent with the range of thin-haul trips. Trips with county-to-county GC distance less than 50 miles and greater than 350 miles were filtered out. As shown in Figure 3.9, more than 3 over 4 trips were covered by automobiles. Considering that, only trips covered by automobile were considered in this research. Leisure and business automobiles passenger flows were added up to compose a unique data of auto demand, and converted to daily passenger demand.

The following step was to add up the automobiles passenger demand of airport-to-airport routes that could have potentially appeared multiple times during the combination of the databases. The complete dataset was further filtered keeping routes that consisted of at least 50 passengers a day [29]. Fewer routes that presented daily air demand greater than five passengers were removed to avoid competition with current air service. The result was a set of 2,094 potential O&D pairs with daily demand varying from 50 to 2,130 passengers, resulting in a total of 329,287, including 141 airports, depicted in Figure 3.10. Albany International Airport (ALB) was selected to be the network hub due to its central location.

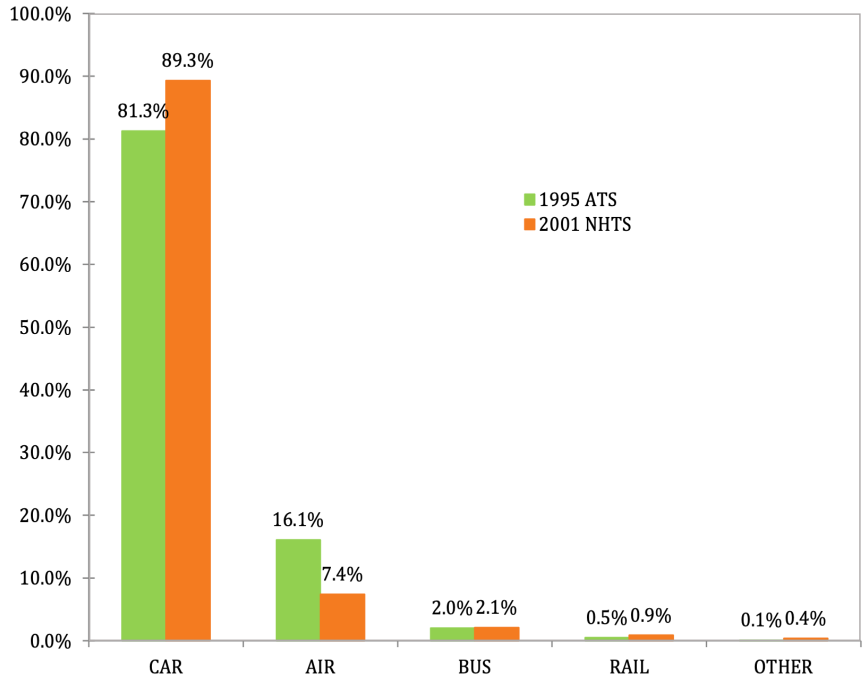


Figure 3.9: Trips distribution by mode of transport [51]

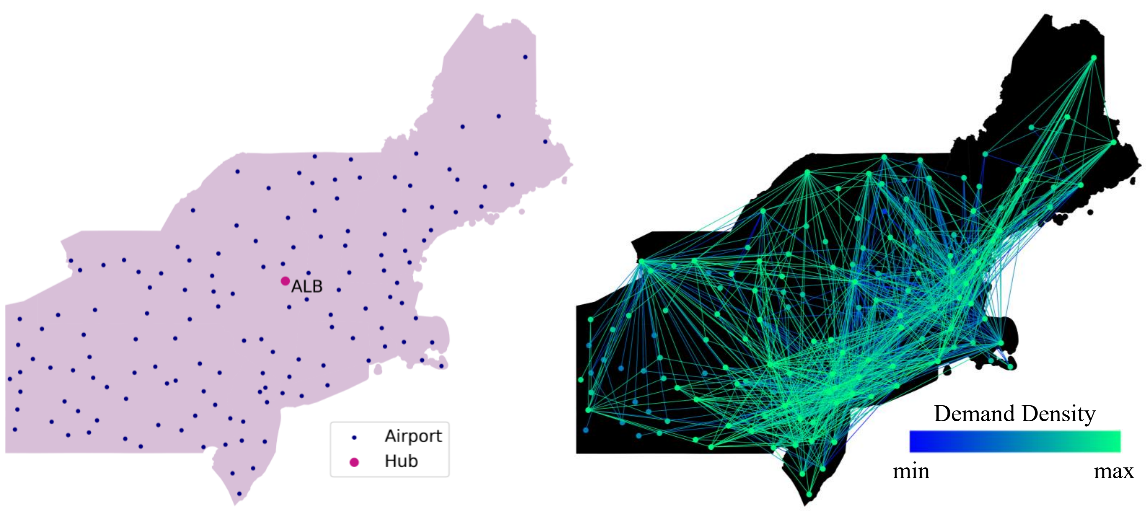


Figure 3.10: Results of trip generation and distribution - *left:* potential airports; *right:* potential routes

The last step was to compute the driving distance from origin county to destination county, as well as from county to airport and vice-versa. *OSMnx* package was adopted to download geospatial maps from *OpenStreetMap*. OpenStreetMap provides detailed uni-directional highway data that was used to compute the shortest path between two geocoordinate points through Dijkstra's algorithm. In this case, the county centroid was adopted as the reference point, since computing the distance from different locations in the county would be too computational expensive. Figure 3.11 shows the complete highway map of the New England and Mid-Atlantic regions, as well as an example of driving path from Philadelphia, PA, to Broome county, NY, with an approximate distance of 177 miles.

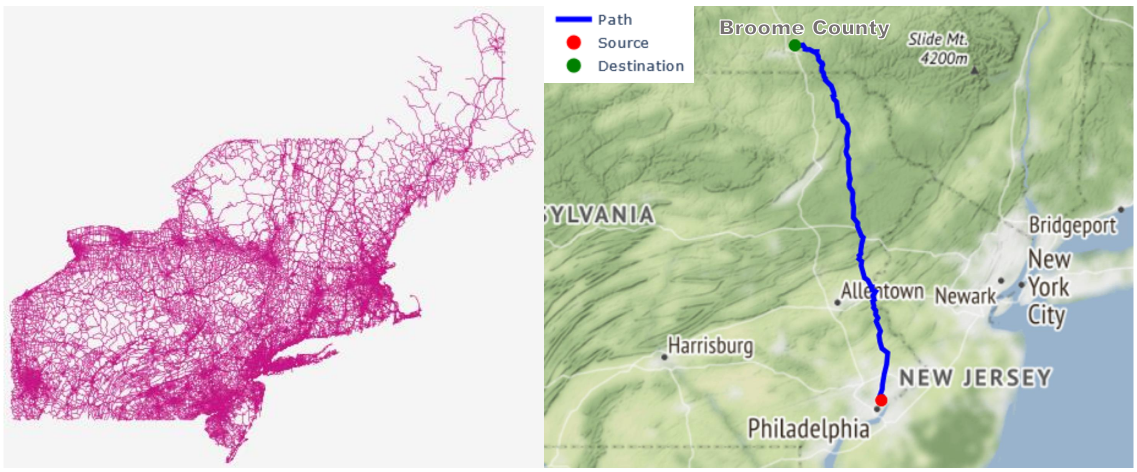


Figure 3.11: *OpenStreetMap* library - *left:* highway map of Northeast USA; *right:* example of driving path from Broome, NY to Philadelphia, PA

3.4.2 Potential Market Share and Itinerary Attractiveness

As described in subsection 3.2.2, the potential market share and the itinerary attractiveness are computed based on the income distribution of passengers and the opportunity cost, that depends on the cost and trip time using air service and an alternative mode of transport. These elements are detailed in the next section.

Ticket price

The ticket price was determined based on the itinerary type using data from *Airline Origin and Destination Survey (DB1B)* database provided by the United States Department of Transportation [52]. This database provides a 10% sample of domestic flight tickets reported by airlines in the USA per quarter. The database is divided in three subsets: Ticket, Market, and Coupon data. Ticket data provides information of the purchased ticket, usually round-trip, including number of itineraries and coupons. Market database is a subset of the ticket database and provides directional market information, such as origin and destination airports, itinerary fare, number of coupons, and total distance flown. Coupon database brings more detailed information about the coupons of the purchased tickets.

The Market database was selected since it specifies detailed information at the itinerary level. The year chosen was 2019 to reflect fares charged previous to the covid-19 pandemic. The data of the four quarters of 2019 were combined and filtered according to distance flown and numbers of coupons. Only data from contiguous domestic flights, i.e., flights between the 48 continental US states was considered. Markets containing one or two coupons were kept, representing non-stop and single connection itineraries respectively. In practice, itineraries can have multiple connections; however, since trips with more than one connection takes longer and are considered noncompetitive time-wise for short-range routes, only non-stop and single connections were considered. Data from markets with distances flown less than 50 miles and greater than 500 miles was disregarded.

To compute the fare, regressions were developed based on the itinerary yield, since the yield data presented a better fit than fare values. For each data point, yield was computed by dividing the market fare by the miles flown. Then, the yield values were averaged among data points with the same miles flown. Nonetheless, the considerable size of the dataset led to the appearance of clusters of points that prevented a good data fit, even considering different types of regression, as shown in Figure 3.12.

To improve the quality of fit, the data points were subsequently grouped by segments of five to five miles and the yield among these groups of points was averaged again to reduce the clusters in the data. Since the data points usually present high values of yield at short distances and low values for longer routes, outliers deviating considerably from this trend were removed. The resulting logarithmic, exponential, and polynomial regressions are depicted in Figure 3.13.

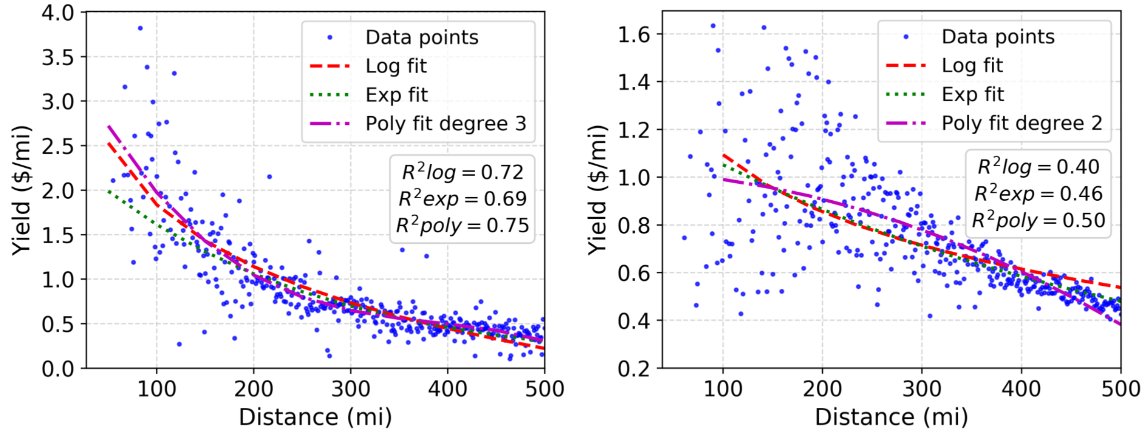


Figure 3.12: Clusters of data points in the yield regression - *left:* non-stop itinerary; *right:* connecting itinerary

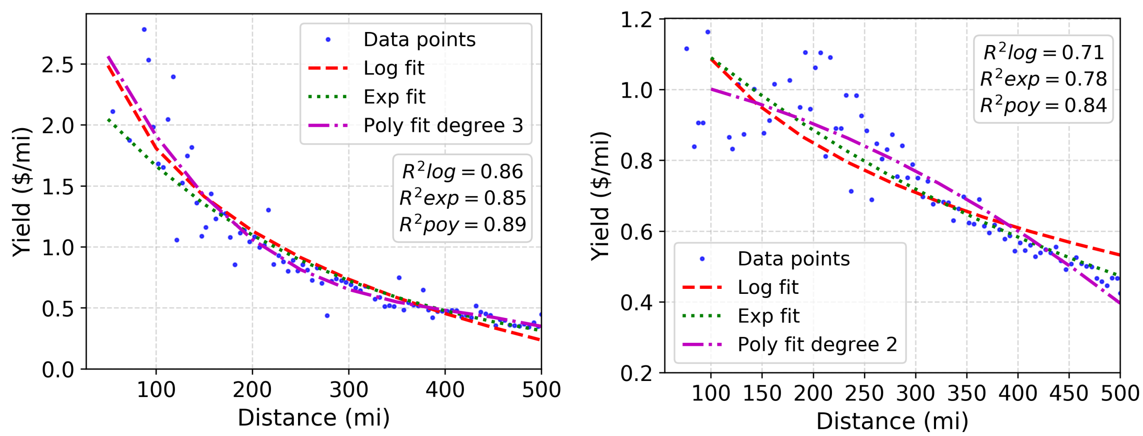


Figure 3.13: Adopted yield regressions - *left:* non-stop itinerary; *right:* connecting itinerary

For both cases, the polynomial regression was selected due to its better fit. The fare can then be computed for any given itinerary *p* with distance flown $dist_p$, according to Equation 3.17, where $dist_p$ corresponds to the sum of the GC distances of all legs that are part of itinerary *p*. If $dist_p$ is greater than 550 miles, then the fare value is set to be equivalent to the fare at 550 miles distance.

$$Fare_p = yield_p \cdot dist_p \tag{3.17}$$

Trip cost and trip time using automobile

The cost to cover a trip using a car ($Cost_{alt}$) is computed based on the average cost of owing and operating an automobile defined by the Bureau of Transportation Statistics [53]. The average cost derived by the American Automobile Association includes fuel cost, maintenance, tires, insurance, license, registration, depreciation, and finance costs, considering a fiver-year and 75,000-miles ownership period. The retrieved average cost was $0.62\$/mile$ per mile for the year of 2019. The total car cost was computed considering the driving distance of each O&D pair determined in subsection 3.4.1.

The trip time ($Time_{alt}$) was calculated considering the average of the speed limit in the state roads, as presented in Table 3.1. An approximate average speed of 60 mph was retained based on the average speed limit of 61.7 mph. Similarly to the cost, the trip time was then computed considering the diving distance determined in subsection 3.4.1.

Table 3.1: Speed Limit by road type in the Northeastern states, in mph (adapted from [54])

State	**Interstate**		**Limited access road**	**Other roads**
	Rural	**Urban**		
Connecticut	65	55	65	55
Maine	75	75	75	60
Massachusetts	65	65	65	55
New Hampshire	65	65	55	55
Rhode Island	65	55	55	55
Vermont	65	55	50	50
New Jersey	65	55	65	55
New York	65	65	65	55
Pennsylvania	70	70	70	55

Trip time and trip cost by air service

The total trip time and cost were computed considering the flight portion of the trip along with the access and egress trip to and from the airport, as depicted in Figure 3.14. According to a study conducted among large airports [55], almost 90% of the passengers use private vehicles or ride-share transport to go to the airport, and roughly 80% of this group use personal vehicles. Considering that, the same car operating cost of $0.62\$/mile$ was adopted. The driving distances from county to airport ($dist_{ac}$) and from airport to county ($dist_{eg}$) were determined similarly to subsection 3.4.1 using *OpenStreetMap*. Therefore, the total cost of flying a given itinerary p was derived according to Equation 3.18.

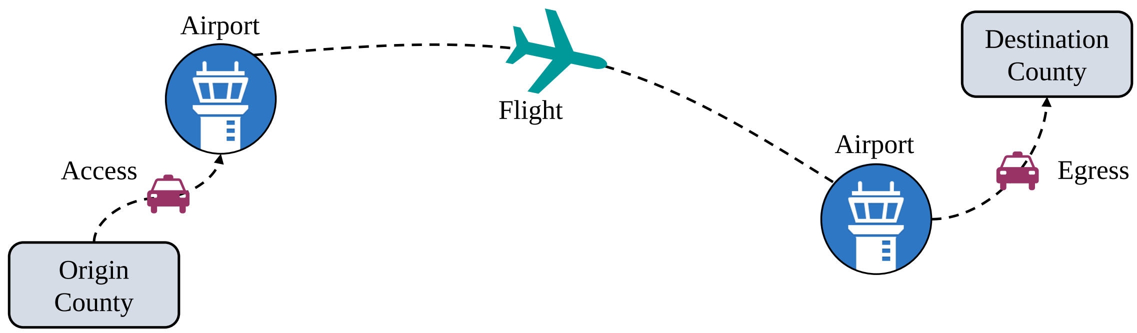


Figure 3.14: Access and egress to and from airport (adapted from [27])

$$Cost_p = Fare_p + c_{a/e} \cdot (dist_{ac} + dist_{eg}) \tag{3.18}$$

where $c_{a/e}$ is the airport access/egress cost.

The trip time computation follows the same structure. The driving speed ($v_{a/e}$) of the access and egress portion of the trip was derived based on the speed limit of residential roads and urban freeways [56], that varies from 25mph to 65 mph. An average value of 45mph was retained. The flight time of each itinerary is less straightforward to calculate because it depends on the fleet assignment process. The fleet assignment, on the other hand, is determined based on the itinerary attractiveness according to the optimization process described in section 3.3, that in turn depends on the flight time, leading to an iterative process. To circumvent that, the flight time was calculated based on an average speed (v_{ac}) and the connection time (t_{connec}), if any. Typical cruise speeds of 6 to 10-seat aircraft used in commuter operations varies from 194 KTAS to 285 KTAS, and advanced concepts are expected to achieve a cruise speed between 180 and 325 KTAS [18]. A lower value of 217 KTAS, or 250 mph, was adopted, considering that climb and descent represent a considerable portion of short range missions and the speed at these phases are somewhat lower. As previously mentioned, the flight distance $dist_p$ is given by the sum of the GC distances of all legs that compose the itinerary. Therefore, the total trip time using air service is defined by Equation 3.19.

$$Time_p = \frac{dist_p}{v_{ac}} + t_{connec} + \frac{(dist_{ac} + dist_{eg})}{v_{a/e}} \tag{3.19}$$

Income distribution

The US Census Bureau provides the annual income distribution of the US households in the national and state level [50, 57]. The database, however, is limited to annual wages of \$200,000, which is equivalent to 96\$/h considering an average workload of 2,080 hours per year. The World Inequality Database [58], on the other hand, provides a complete distribution for the USA for different income classifications, but not at the state level.

Figure 3.15 shows a comparison between two WID US data for the year of 2014, considering pre-taxes and post-taxes incomes, and the Census state data for the same year, in which the incomes were converted to $\$/h$ representing the passengers' VTTS. The WID US incomes were combined assuming that post-tax illustrates leisure travelers and pre-tax represents business travelers, and considering a share of 40.6% for business travels and 59.4% for leisure travels [59]. The income distributions of the Northeastern states and the US have a similar shape, with the combined US distribution presenting values closer to the state-level ones. Therefore, the US income distribution was adopted as the representative value of the Northeastern state wages.

Figure 3.16 depicts the complete combined USA income distribution. The values were corrected to reflect the dollar value of 2019 based on a consumer price index (CPI) of 1.09, considering 2014 as the reference year [60]. The cumulative number of adults was computed considering the USA adults population of 2014, equal to 230,048,656 people, or potential passengers.

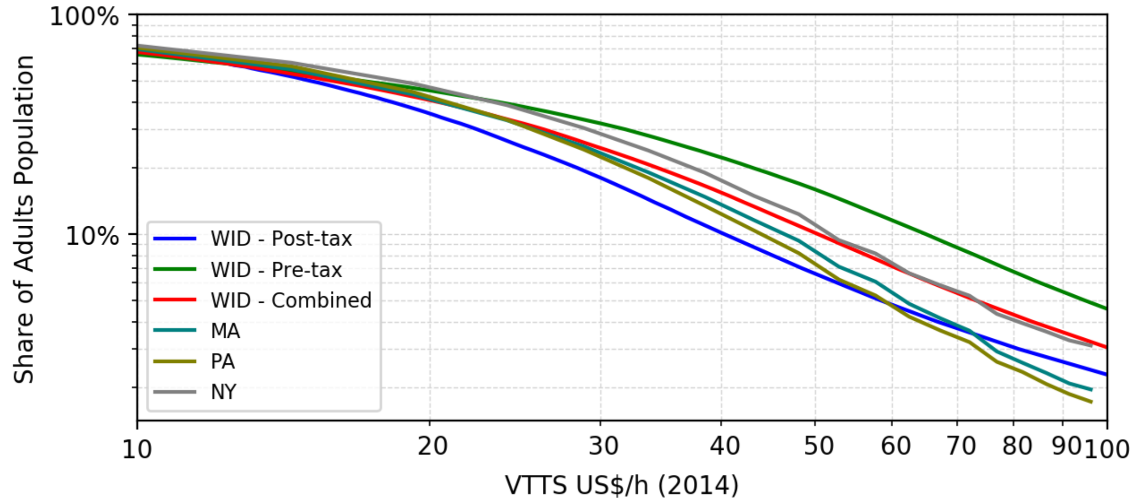


Figure 3.15: Comparison between income distribution of the US and Northeastern states

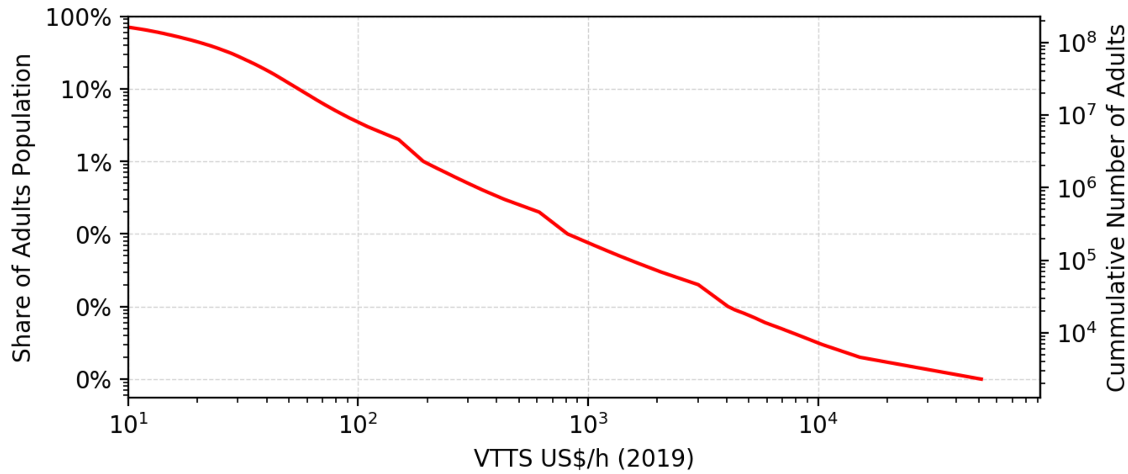


Figure 3.16: Combined US income distribution corrected to 2019 dollar value

3.4.3 Thin-haul ITD-FA Model

Assumptions

The ITD-FA model applied to thin-haul operations was implemented considering the following assumptions:

- Daily schedule that repeats itself every day. This implies that Equation 3.9 must be reinforced, i.e., the airport must have the same number of aircraft of each type in the beginning and in the end of the day;

- Time window of 30 minutes;

- A maximum of two legs for each itinerary. As previously mentioned, paths with more than one connection take longer and are considered non-competitive for short-range routes. In this case, having more than one hub in the network will only increase the number of possible itineraries for a certain route;

- Three types of itineraries: non-stop itinerary, with one flight leg, short-connection itinerary, with two flight legs and a connection of 30 minutes, and long-connection itinerary, with two flight legs and connection time of one hour;

- The aircraft turnaround time is assumed to be 30 minutes, the same duration of the short connection. Therefore, for the short-connection itinerary, the departure node of the second leg is the same as the arrival node of the first leg;

- Limited hours of operations, from 5am to 10pm, with no overnight connections;

- Flight legs with minimum distance of 30 miles;

- Itineraries with opportunity cost greater than 1,000$/h and less than 10% of time saved are also considered noncompetitive and therefore are disregarded;

- If an itinerary presents a negative $\Delta Time$, i.e., it takes more time to fly the itinerary than to drive, the itinerary attractiveness is set to zero by defining a symbolic value of $\Delta Cost/\Delta Time$ equivalent to 10^8 $/h.

Hourly trip distribution

In the literature, most studies focus on determining the time-of-day preference of urban trips. Fujita et al. [61] estimated time coefficient of hourly demand distribution based on traffic predictions for Chukio metropolitan area in Japan. Pendyala [62] modeled time of day of trips done in the main metropolitan areas of Florida for different trip purposes. A similar study was performed at the USA level by the Bureau of Transportation Statistics [63]. These studies demonstrate that the overall daily trips in urban areas present distinct peaks in the morning, afternoon, and night hours, and that these peaks are even more evident in commuter trip to and from work, as depicted in Figure 3.17.

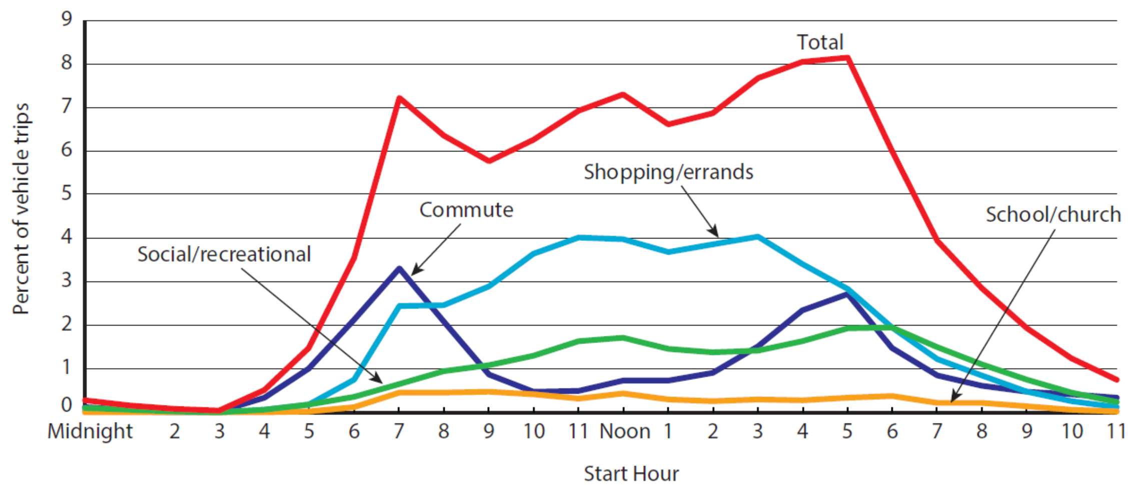


Figure 3.17: Hourly trip distribution in urban areas in the USA [63]

One of the few studies attempting to model time-of-day choice for long-distance trips was conducted by Jin et al. [64], considering trip distances from 50 to 1,200 miles. The authors adopted the same long-distance trip database used to build the Traveler Analysis Framework. The database was integrated to a survey with 14 passengers to capture hourly preferences, since the database does not provide this type of information. The study brings important conclusions regarding preference on the departure time for different trip purposes, such as business travelers preference for morning and afternoon peaks, and the option for hours without traffic congestion. Nonetheless, the study was limited to a low-fidelity discrete distribution with only six time intervals among the 24 hours of the day. Besides, the results reflect distribution of trips accumulated from different days of the week, including weekdays and weekends, and cannot be compared with a common daily distribution as presented in Figure 3.17.

Thin-haul operations are expected to attract mainly passengers travelling for work purposes, personal business, and occasionally for leisure. In these cases, there is prevailing preference for early morning or afternoon flights, specially for business travels and when highway congestion is not an issue. In the absence of a high-fidelity model of time-of-day preference for intercity trips, the hourly distribution was modeled following the detailed discrete distribution of work trips for Tampa Bay [62]. The distribution is also similar to the predicted preference by morning and late afternoon peaks of passengers flying short-range hours [31].

The hourly trip distribution was converted to a discrete *bimodal distribution*, as shown in Figure 3.18. Continuous bimodal distributions are modeled according to Equation 3.20, where ϕ_1 and ϕ_2 are the two *normal distributions* and w is the split rate between these two distributions.

$$f(x) = w\phi_1(x) + (1 - w)\phi_2(x) \tag{3.20}$$

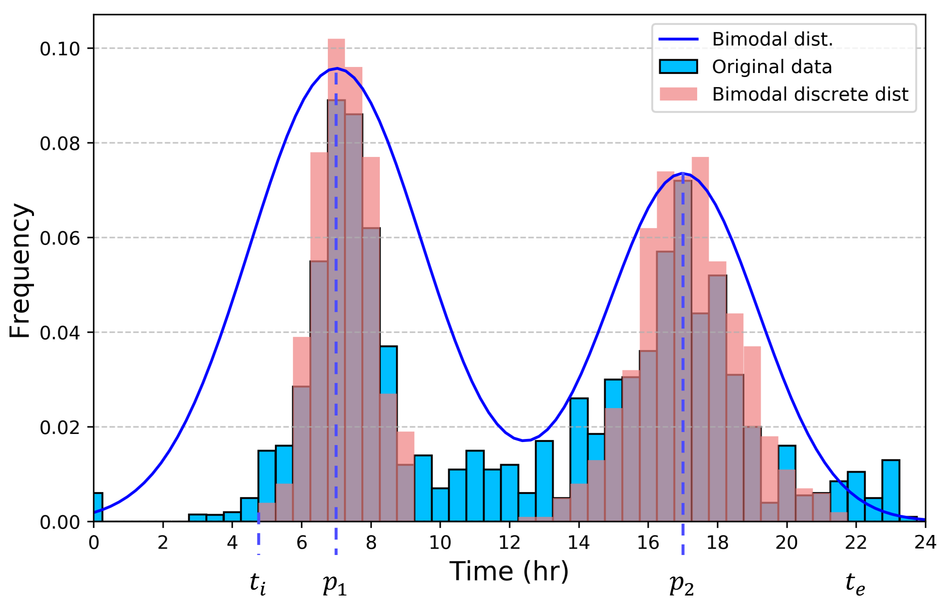


Figure 3.18: Bimodal normal distribution

The hourly distribution was implemented as a discrete function, requiring as inputs the initial (t_i) and final (t_e) hours of operations, the expected morning (p_1) and night (p_2) peaks, and the split rate between the two bimodal distributions. The distribution was defined by selecting their means at the peak hours, while the standard deviations were computed based on the time difference between the peaks and the initial/final hours of operations. The distribution was then linked to the time-window discrete periods to define the frequency of trips at each potential departure time.

Therefore, the model can be easily adapted for different hours of operations, time window values, peak hours, and split rates. It can also be developed for different distribution shapes, such as Weibull and beta distributions, and for distinct distributions among the routes. Nonetheless, in this thesis the distribution was assumed to be the same bimodal normal distribution throughout all the routes, with peaks at 7am and 5pm, initial time at 5am, and final time at 22pm, as represented in Figure 3.18.

Fleet data

The selected fleet is composed by two retrofitted aircraft types, a 9-seat electric P2012 and a 48-pax hybrid-electric ATR 42 models developed by Oliveira et al. [48]. These two seat capacities were chosen because the 9-pax vehicle allows the transport of fewer passengers more efficiently, while the 48-pax aircraft class allows more passengers to be transported when aggregated at hubs. Each aircraft is represented by surrogate models that calculate its performance characteristics and the direct operating cost (DOC) per mile. The final $DOC_{f,t,k}$ for each leg was then computed considering the GC distance $dist_f$ between the airports of the flight leg f.

While the hybrid-electric ATR 42 was redesigned for a fixed range of 345 miles, the design range of the electric P2012 depends on the battery specific energy density (BSED) assumptions. The technological assumptions were based on the year of 2030, when hybrid-electric and electric propulsion systems are expected to have reached technology maturity [65]. With the exception of the BSED, these assumptions were the same ones adopted by

Oliveira et al. [48] and are listed on Table 3.2.

Table 3.2: Assumptions for the year of 2030 (retrieved from [48])

Technological Assumptions		**Economic Assumptions**	
Battery Discharge Life Cycle $(cycles)$	2000	Electricity Rates $(cents/kWh)$	14.5
Hybridization Level $(\%)$	75	Specific Battery Cost $(\$/kWh)$	90
Electricity Production Emissions (gCO_2/kWh)	272	Fuel Price $(\$/US\ gallon)$	3.85

The values of BSED were retrieved from a recent study developed by the Washington State Department of Transportation [66]. According to the report, battery technologies are expected to reach an energy density level between 400 and 450 Wh/kg by the mid-2020's. For the P2012, the higher the values of BSED, the higher the range of the aircraft. Nonetheless, the DOC surrogates for both aircraft and the P2012 range surrogate are limited to a value of 400 Wh/kg, which results in a P2012 range of only $183.6\ mi$. Figure 3.19, however, shows that the P2012 surrogates can be safely extrapolated up to 450 Wh/kg, since the responses are still smooth and follow the trends. Therefore, a BSED value of 400 Wh/kg was retained for the hybrid-electric ATR 42 and a value of 450 Wh/kg for the electric P2012, resulting in a range of $225\ mi$.

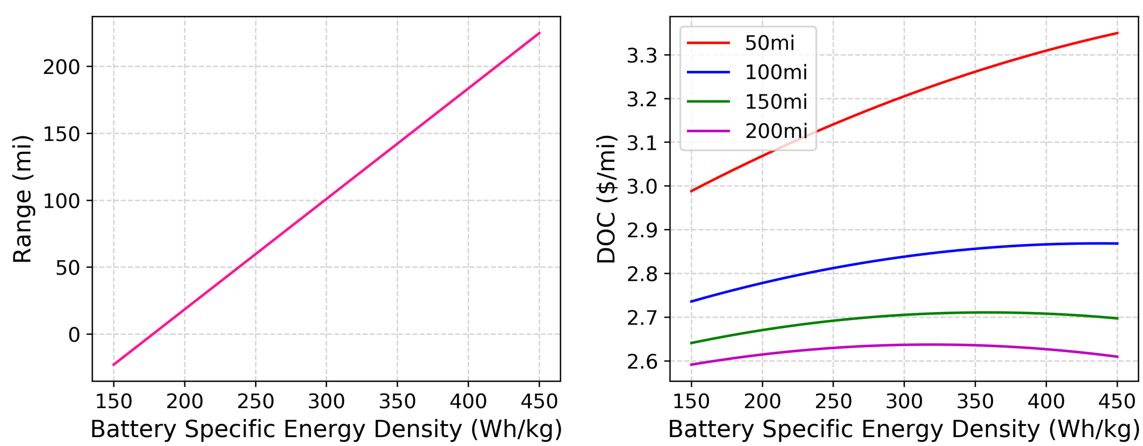


Figure 3.19: Electric P2012 surrogates - *left:* range; *right:* DOC per mile

The daily unit cost of the aircraft, used as part of the penalty function in Equation 3.6, were computed based on methods documented by Roskan [67]. This cost represents the daily payment airlines need to cover when leasing a vehicle, and it depends on the aircraft acquisition cost Acq_k, the depreciation rate R_{dep}, the annual loan rate R and loan time n, and the annual insurance rate R_{ins}. Equation 3.21 to Equation 3.24 detail the computation of the daily unit cost.

$$Dep = Acq_k \cdot R_{dep} \tag{3.21}$$

$$Annual\ Pay = Dep \cdot \frac{R(1+R)^n}{(1+R)^n - 1} \tag{3.22}$$

$$Ins = Acq_k \cdot R_{ins} \tag{3.23}$$

$$UP_k = \frac{Annual\ Pay + Ins}{365} \tag{3.24}$$

To be consistent, the same values used to develop the surrogates were adopted: 5% loan rate for 10 years, 1% of insurance rate, a depreciation of 80% in the total unit cost, and acquisition costs of US$1.5 million and US$12 million for the P2012 and the ATR 42, respectively [48]. The daily unit cost, as well as the other aircraft attributes, are detailed in Table 3.3.

Table 3.3: Aircraft attributes

	P2012	**ATR 42**
Range in mi ($Range_k$)	225	345
Capacity (Cap_k)	9	48
TOFL in ft ($TOFL_k$)	3,000	4,250
Unit Cost in \$/day (UP_k)	467	3,766

Concept of Operations

The framework was developed to handle three types of network: point-to-point, hub-and-spoke, and hybrid network. Point-to-point networks have exclusively non-stop flights, and therefore only one type of itinerary. Hub-and-spoke networks have only itineraries through hubs, in which case short and long-connection itineraries may be available for passengers. Routes in which the hub is either an origin or a destination airport represent an exception, with only non-stop itineraries available in this case. At last, hybrid networks have both non-stop, short, and long-connection itineraries. Figure 3.20 depicts the three type of network available.

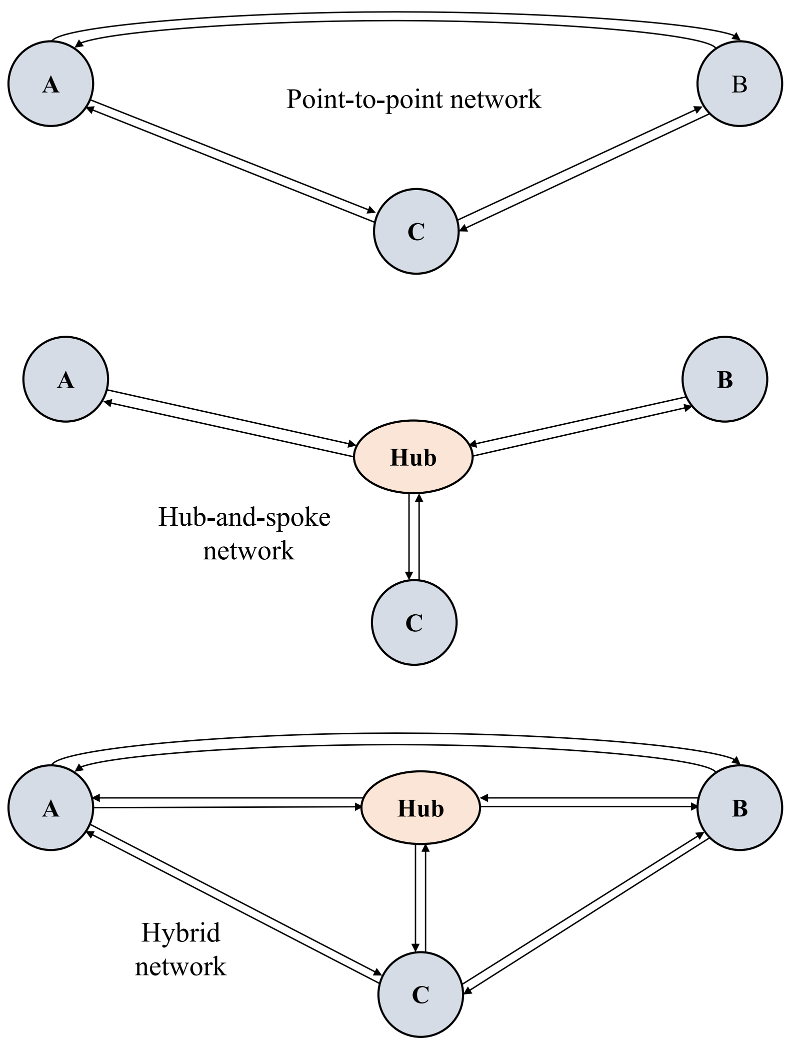


Figure 3.20: Type of network structures

Optimization Environment

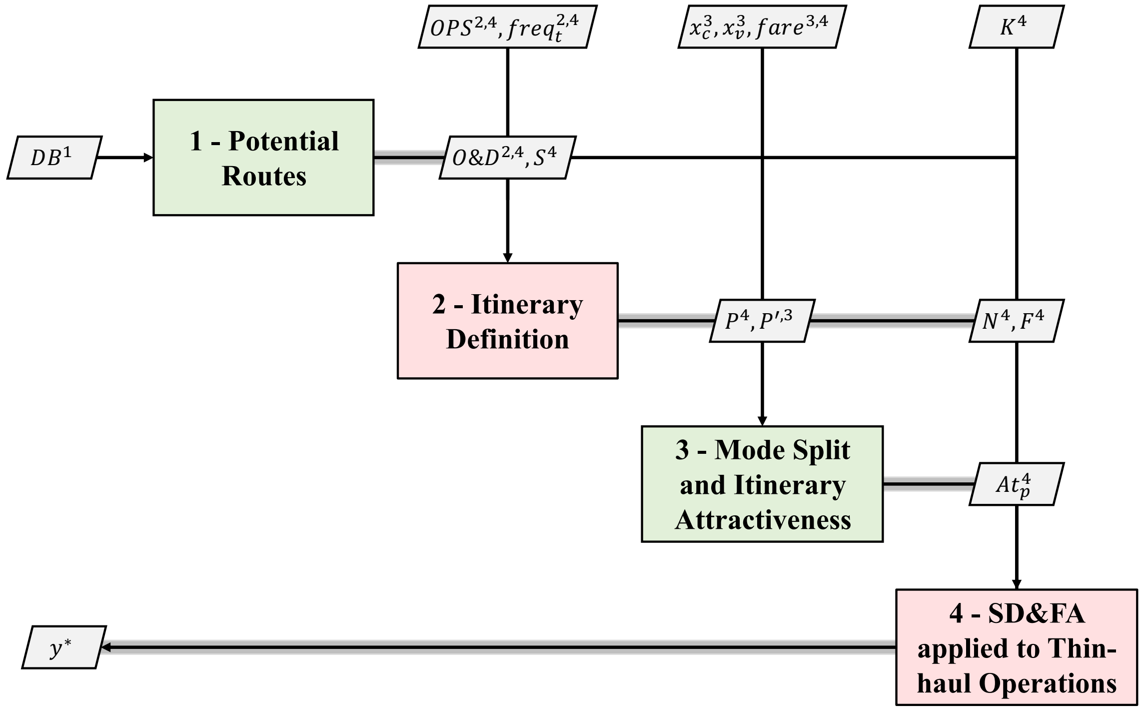
The adapted ITD-FA model described in section 3.3 is solved using *Gurobi Optimizer* [68] package for *python*. *Gurobi* is a fast and powerful commercial optimizer that is able to handle problems with an extensive number of design variables within reasonable time. The problem was modeled using object-oriented programming to facilitate the representation of the set elements and their specific attributes.

In order to reduce the size of the problem, in addition to the assumptions listed on subsubsection 3.4.3, itineraries with less than one passenger demand were removed. This includes removing itineraries with no significant time savings when compared to ground transport. In addition, Equation 3.12 and Equation 3.13, regarding the aircraft range and TOFL limitations, were enforced in the pre-processing phase to reduce the design variables domain and speed up the optimization. In this case, since it might not be possible to cover all flight legs, the set F is replace by the subset F' considering the possible flights (f, t).

Another strategy adopted to reduce the running time was to set up a value for the optimality gap tolerance. In *Gurobi*, this is done through the $MIPGap$ *parameter*. The $MIPGap$ allows the solver to *"terminate with an optimal result when the gap between the lower and upper objective bound is less than* $MIPGap$ *times the absolute value of the incumbent objective value*" [68]. For maximization problems, the incumbent objective value is the lower bound. Unless otherwise specified, a $MIPGap$ value of 0.1% is adopted. Moreover, the search for the optimum solution is limited to four hours.

3.5 Framework Structure

Figure 3.21 depicts a structural representation of the framework, adapted to demonstrate the relationship between the analysis, the main given inputs, and the output of each step. The superscript in each attribute is used to better link the inputs to their respective processes.



$\boldsymbol{DB}$ – county-to-county trips, airport, and county databases, and geospatial library

$\boldsymbol{OPS}$ – network structure, operation hours (t_i, t_e), time window, peak hours (p_1, p_2), connection time (t_{connec})

$\boldsymbol{freq_t}$ – hourly trip distribution

$\boldsymbol{O\&D}$ – potential routes with daily demand ($Dem_{O\&D}$) and county-to-county highway distance

$\boldsymbol{S}$ – potential airports with county-airport highway distance ($dist_{ac}, dist_{eg}$) and runway length (Rw_s)

$\boldsymbol{x_c}$ – car operating cost, egress/access cost ($c_{a/e}$)

$\boldsymbol{x_v}$ – driving speed between cities, egress/access speed ($v_{a/e}$), aircraft average speed (v_{ac})

$\boldsymbol{fare}$ – fare regressions

$\boldsymbol{P}$ – set of itineraries and their distance ($dist_p$)

$\boldsymbol{P'}$ – subsets of itineraries for each $O\&D$ pair, each departure time

$\boldsymbol{K}$ – set of aircraft type with seat capacity (Cap_k), direct operating cost ($DOC_{f,t,k}$), takeoff field length ($TOFL_k$), range ($Range_k$) and daily unit price (UP_k), turnaround time

$\boldsymbol{N}, \boldsymbol{F}$ – set of nodes and flight legs with distance of each leg ($dist_f$)

$\boldsymbol{At_p}$ – attractiveness of each itinerary

$\boldsymbol{y^*}$ – metrics of effectiveness

Process flow; output from an analysis

Figure 3.21: Framework Structure

CHAPTER 4

HYPOTHESIS TESTING

In this chapter, hypotheses 1 and 2 are substantiated following the experimental plans described in chapter 2.

4.1 Hypothesis 1 Testing

Recalling from section 2.1, **HP1** states that *if choice of mode and itinerary attractiveness techniques are combined, while accounting for competition with alternative modes of transport, then thin-haul passenger demand at the itinerary-level can be quantified with medium fidelity*. In order to substantiate it, the designed experiments propose to test the methodology detailed in subsection 3.2.2 against the traditional MNL models and the opportunity cost approach, considering the established criteria.

The experiments were conducted in a subset of three routes: from Boston Airport, MA (BOS) to Plattsburgh Airport, NY (PBG), from Piseco Airport, NY (K09) to LaGuardia Airport, NY (LGA), and from Rutland–Southern Airport, VT (RTU) to LaGuardia. Albany Airport, NY (ALB) was adopted as a hub. The routes are detailed in Figure 4.1. The trip cost and time of the three routes when covered by car were computed according to subsection 3.4.2, and are detailed in Table 4.1.

Table 4.1: Routes attributes for the driving option

Route	Distance (mi)			Trip Time (h)	Trip Cost ($)
	County to county	County-Apt			
		County-Apt DEP	Apt-County ARR		
BOS - PBG	275.9	3.6	18.2	4.6	171.1
K09 - LGA	273.0	1.9	8.9	4.6	169.3
RUT - LGA	224.4	9.2	8.9	3.7	139.1

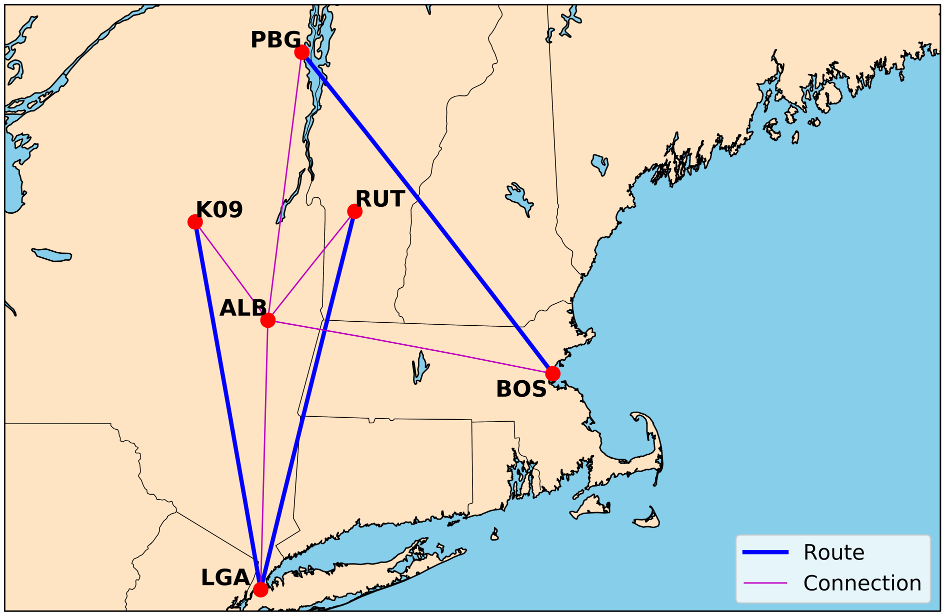


Figure 4.1: Set of routes for experiment 1

The network structure adopted was the hybrid one, resulting in three potential itineraries for each departure time. The trip cost and time when flying each one of the potential itineraries were also computed according to subsection 3.4.2. With these values, the opportunity cost of each itinerary was determined. The results for the set of routes are detailed on Table 4.2, Table 4.3, and Table 4.4.

Table 4.2: Itinerary attributes of route BOS - PBG

Itinerary	**Non-Stop**	**Short**	**Long**	**Total**
$Time$ (h)	1.3	2.1	2.6	-
$Cost$ (\$)	225.7	236.4	236.4	-
$\Delta Time$ (h)	3.3	2.5	2.0	7.8
$\Delta Cost$ (\$)	54.6	65.3	65.3	185.2
$\Delta Cost/\Delta Time$ (\$/h)	16.5	26.1	32.6	75.1

As previously mentioned, the opportunity cost represents how much a passenger would have to pay for one hour of time saved. The lower the opportunity cost, the more attractive the itinerary. Note that this subset of routes presents the three possible rankings between

Table 4.3: Itinerary attributes of route K09 - LGA

Itinerary	**Non-Stop**	**Short**	**Long**	**Total**
$Time$ (h)	1.0	1.5	2.0	-
$Cost$ ($)	220.2	185.3	185.3	-
$\Delta Time$ (h)	3.6	3.0	2.5	9.1
$\Delta Cost$ ($)	51.0	16.0	16.0	83.0
$\Delta Cost/\Delta Time$ ($/h)	14.3	5.3	6.4	26.0

Table 4.4: Itinerary attributes of route RUT - LGA

Itinerary	**Non-Stop**	**Short**	**Long**	**Total**
$Time$ (h)	1.2	1.7	2.2	-
$Cost$ ($)	223.9	195.5	195.5	-
$\Delta Time$ (h)	2.6	2.0	1.5	6.1
$\Delta Cost$ ($)	84.8	56.4	56.4	197.5
$\Delta Cost/\Delta Time$ ($/h)	33.2	27.9	37.1	98.3

the itineraries of a route: one in which the non-stop itinerary has the lowest opportunity cost, another one in which this itinerary presents the intermediate value, and a third one with the non-stop alternative presenting the highest opportunity cost. These scenarios are represented by routes BOS-PBG, RUT-LGA, and K09-LGA, respectively.

4.1.1 Step 1 - MNL Model

As described in section 2.1, the first step of the experimental plan consists of determining the potential market share and the itinerary attractiveness using a typical utility function, with the opportunity cost as the parameter that drives passenger decisions in the thin-haul market. The utility function is described by Equation 2.2, while the attractiveness is the probability of a passenger choosing an alternative based on its utility, according to Equation 2.1. Then, for this step of the experimental plan, the utility function and the attractiveness are represented by Equation 4.1 and Equation 4.2. The opportunity costs were normalized to be represented by relative values between 0 and 1.

$$u_p = e^{-\alpha \cdot \left(\overline{\Delta Cost/\Delta Time}\right)_p}, \qquad \forall p \in P' \tag{4.1}$$

$$At_p = \frac{u_p}{\sum_p u_p}, \qquad \forall p \in P' \tag{4.2}$$

Values for the coefficient α can be assumed in the absence of resources and data to properly determine it. The itinerary utilities were computed for three different values of the coefficient α: 1.0, 3.0, and 5.0. The results for the three routes are shown in Table 4.5, Table 4.6, and Table 4.7.

Table 4.5: Itinerary utilities and attractiveness of route BOS - PBG

	Itinerary	**Non-stop**	**Short**	**Long**	**Total**
	$\overline{\Delta Cost/\Delta Time}$	0.22	0.35	0.43	-
$\alpha = 1.0$	u_p	0.80	0.71	0.65	2.16
	At_p	37%	33%	30%	100%
$\alpha = 3.0$	u_p	0.52	0.35	0.27	1.14
	At_p	45%	31%	24%	100%
$\alpha = 5.0$	u_p	0.33	0.18	0.11	0.62
	At_p	53%	28%	18%	100%

Table 4.6: Itinerary utilities and attractiveness of route K09 - LGA

	Itinerary	**Non-stop**	**Short**	**Long**	**Total**
	$\overline{\Delta Cost/\Delta Time}$	0.55	0.20	0.24	-
$\alpha = 1.0$	u_p	0.58	0.82	0.78	2.17
	At_p	26%	37%	36%	100%
$\alpha = 3.0$	u_p	0.19	0.54	0.48	1.21
	At_p	16%	45%	39%	100%
$\alpha = 5.0$	u_p	0.06	0.36	0.29	0.72
	At_p	9%	50%	41%	100%

The experiment demonstrated that the itinerary attractiveness is sensitive to the values of the coefficient α. Different assumptions led to substantially different attractiveness

Table 4.7: Itinerary utilities and attractiveness of route RUT - LGA

	Itinerary	Non-stop	Short	Long	Total
	$\overline{\Delta Cost/\Delta Time}$	0.34	0.28	0.38	-
$\alpha = 1.0$	u_p	0.71	0.75	0.69	2.15
	At_p	33%	35%	32%	100%
$\alpha = 3.0$	u_p	0.36	0.43	0.32	1.11
	At_p	33%	38%	29%	100%
$\alpha = 5.0$	u_p	0.18	0.24	0.15	0.58
	At_p	32%	42%	26%	100%

values. To mitigate the uncertainty in the attractiveness computation, MNL models are calibrated using large databases, empirical data, and statistical software to accurately determine the coefficients. As previously mentioned, this can be prohibitive for the thin-haul market due to the lack of available data. In addition, the process is often time-consuming and involved. Therefore, the approach proposed by *step 1* failed to meet the established criteria, that seeks for a methodology with limited implementation time that does not require calibration.

Furthermore, the previous calculations only determined the itinerary attractiveness; in this case, the potential thin-haul market share must be known. The MNL model could be adapted to also determine the market share if a utility function in the form $u_p = \alpha \cdot Cost + \beta \cdot Time$ was adopted and the automobile option was accounted as another possible itinerary. Nonetheless, this utility function presents two coefficients, which increases the uncertainty and the need for calibration to achieve accurate results.

4.1.2 Step 2 - Opportunity Cost combined with Income Distribution at the Itinerary Level

Since MNL models require calibration, another potential solution would be to adopt the same approach proposed by Paproth et al. [29] at the itinerary level. In this case, the opportunity cost of each itinerary is compared to the traveler's income distribution, represented by Figure 3.16. Itineraries are then ranked based on the opportunity cost, as shown in Figure 3.4, to determine their *relative switching percentage* ($Perc_p$), given by Equation 3.2. The relative switching percentage replaces the itinerary attractiveness that was computed as a probability in *step 1*. The sum of the relative switching percentages represents the potential market share. Table 4.8, Table 4.9, and Table 4.10 present the results for the three routes.

Table 4.8: Relative switching percentage of route BOS - PBG

Itinerary	$\Delta Cost/\Delta Time$	$\%$ *of population*	$Perc_p$
Non-stop	16.5	52%	18%
Short	26.1	34%	9%
Long	32.6	25%	25%
		Market Share	52%

Table 4.9: Relative switching percentage of route K09 - LGA

Itinerary	$\Delta Cost/\Delta Time$	$\%$ *of population*	$Perc_p$
Non-stop	14.3	58%	58%
Short	5.3	85%	3%
Long	6.4	82%	24%
		Market Share	85%

Table 4.10: Relative switching percentage of route RUT - LGA

Itinerary	$\Delta Cost/\Delta Time$	$\%$ *of population*	$Perc_p$
Non-stop	33.2	24%	4%
Short	27.9	31%	7%
Long	37.1	20%	20%
		Market Share	31%

The experiment demonstrated that applying the methodology proposed by Paproth et al. [29] at the itinerary level yields low fidelity results. With this approach, itineraries with higher values of opportunity cost resulted in higher attractiveness. In fact, these itineraries are less appealing to passengers and therefore must present lower attractiveness. Hence, although this method does not require data for calibration and can determine the market share, the results at the itinerary level were not representative, demonstrating poor fidelity and therefore not meeting the established criteria.

4.1.3 Step 3 - Proposed Approach by Hypothesis 3

Except for the low fidelity, applying the opportunity cost at the itinerary level nearly met the criteria. **HP 1** proposes to improve the fidelity level of *step 2* by integrating it with *step 1*. In this case, the relative switching percentage is combined with a *sub-attractiveness* to compute the overall attractiveness of each itinerary. Instead of using a utility function that requires calibration, the sub-attractiveness is defined as being proportional to the time savings of each itinerary, according to Equation 3.3. Since the sub-attractiveness depends on only one parameter, calibration is not necessary. The itinerary attractiveness is then determined by Equation 3.4. Recapping:

$$at_{p_{i-j}} = \frac{\Delta Time_{p_j}}{\sum \Delta Time_{p_j}}, \quad \forall p_j \in P_i'$$

$$At_p = At_{p_j} = \sum Perc_i \cdot at_{p_{i-j}}$$

where P_i' represents the subset of itineraries that present $\Delta Cost/\Delta Time$ equal or lower than the one of itinerary p_i. A detailed explanation is presented in subsection 3.2.2.

Table 4.11, Table 4.12, and Table 4.13 show the results for the three routes. The potential market share is the same as the one determined in *step 2*. Nonetheless, the itinerary attractiveness now present results consistent with the values of $\Delta Cost/\Delta Time$. Note that the total market share is equivalent to both the sum of the relative switching percentages and the sum of the itinerary attractiveness. Besides, for route BOS - PBG, the non-stop alternative fell in the exception, presenting both the lower opportunity cost and the higher time savings. In this case, its attractiveness was equivalent to the route market share, as described in subsection 3.2.2.

Table 4.11: Itinerary attractiveness of route BOS - PBG using HP1

Itinerary Order	$\Delta Cost$ / $\Delta Time$	$Perc_p$	*Allowed Itineraries*	$\Delta Time(h)$	$at_{p_{i-j}}$	At_p
Non-stop	16.5	18%	Non-stop	3.3	1.0	52%
Short	26.1	9%	Non-stop	3.3	0	0
			Short	2.5	0	
Long	32.6	25%	Non-stop	3.3	0	0
			Short	2.5	0	
			Long	2.0	0	
				Market Share		52%

Table 4.12: Itinerary attractiveness of route K09 - LGA using HP1

Itinerary Order	$\Delta Cost$ / $\Delta Time$	$Perc_p$	*Allowed Itineraries*	$\Delta Time(h)$	$at_{p_{i-j}}$	At_p
Short	5.3	3%	Short	3.0	1.0	35%
Long	6.4	24%	Short	3.0	0.55	27%
			Long	2.5	0.45	
Non-stop	14.3	58%	Non-stop	3.6	0.39	23%
			Short	3.0	0.33	
			Long	2.5	0.28	
				Market Share		85%

Table 4.13: Itinerary attractiveness of route RUT - LGA using HP1

Itinerary Order	$\Delta Cost$ / $\Delta Time$	$Perc_p$	*Allowed Itineraries*	$\Delta Time(h)$	$at_{p_{i-j}}$	At_p
Short	27.9	7%	Short	2.0	1.0	15%
Non-stop	33.2	4%	Non-stop	2.6	0.56	11%
			Short	2.0	0.44	
Long	37.1	20%	Non-stop	2.6	0.42	5%
			Short	2.0	0.33	
			Long	1.5	0.25	
				Market Share		31%

By combining the approach proposed in *step 2* with the sub-attractiveness, the lower the itinerary opportunity cost, the higher its attractiveness. Therefore, the method presented the expected relationship between opportunity cost and attractiveness. In addition, the model adopted to compute the sub-attractiveness did not require calibration. As a consequence, the proposed approach is the one that meets the established criteria, i.e., it captures both the market share and the itinerary choice while keeping medium fidelity and reduced implementation time, without requiring data for calibration.

4.2 Hypothesis 2 Testing

From section 2.2, hypothesis 2 stated that *current ITD-FA models can be adapted to support thin-haul scheduling decisions if the relationship between hourly demand distribution and flight schedule is captured considering the competition with alternative modes of transport*. To substantiate **HP2**, the experimental plan proposes to test the adapted ITD-FA described in subsection 3.4.3 combined with an hourly trip distribution and considering a given potential market share and fixed attractiveness for all itineraries. The adopted distribution is depicted in Figure 3.18. A potential market share of 15% was assumed across all routes. For any O&D pair, itineraries with the same departure time were set to have equal attractiveness. For instance, if a route has three potential itineraries at departure time t, then each itinerary would present an attractiveness equal to $0.15 \cdot 1/3 = 0.05$.

Figure 4.2 shows the cumulative number of passengers transported across all itineraries by departure time. Since the trip distribution describes the preferable departure times from the passengers' point of view, the transit of passengers along the day followed the adopted distribution. Figure 4.3 reveals that the flight departures across the network were highly affected by the passenger preference as well, closely reflecting the demand distribution. Nonetheless, the flight connections and aircraft re-assignment to multiples flights, that are part of the SD&FA process, also impacted the departure times. For instance, flights departing when the input frequency was zero, i.e., between 9:30am and 10:30am, represent connecting flights that do not generate demand. When these flights are excluded, the departure distribution no longer presents any flights in this time range, as shown in the right plot of Figure 4.3. Therefore, the adapted ITD-FA model proposed in subsection 3.4.3, when combined to an hourly trip distribution, could successfully perform the schedule design.

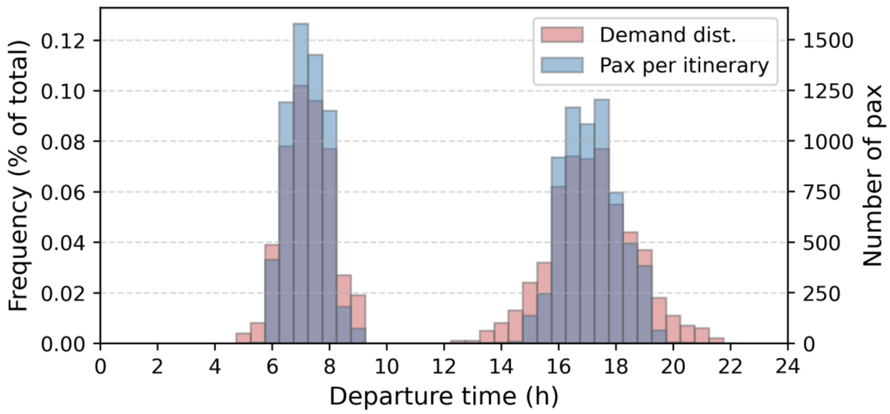


Figure 4.2: Distribution of passengers served at the itinerary level

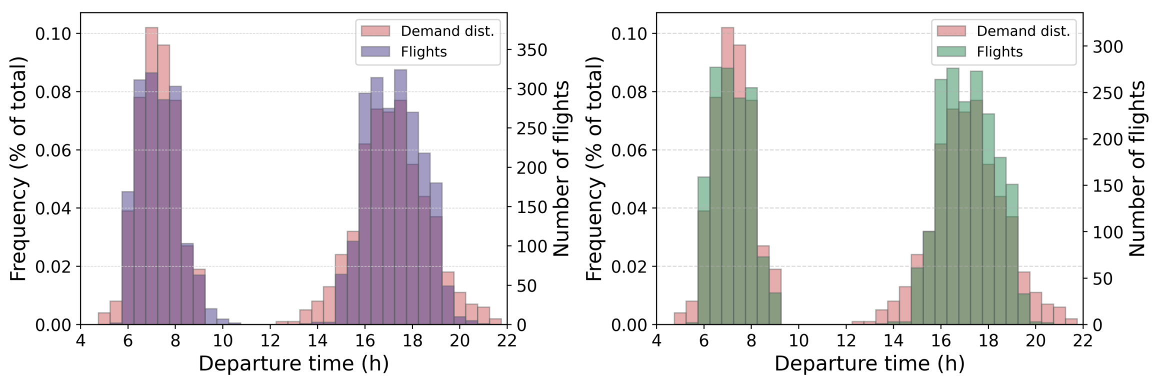


Figure 4.3: Distribution of flights per departure time - *left:* all flights; *right:* excluding connecting flights

Furthermore, the approach proposed by **HP2** was capable of providing the metrics of effectiveness, represented by the operating profit, the number of passengers transported, and the routes and airports served, as listed in Table 4.14. The total run time was approximately 2 hours for a total of 54,045 design variables. The total profit detailed in the table represents the value of the objective function without the penalty component, i.e., without the total daily loan cost, since the ownership cost per mile is already embedded in the surrogate models of the DOC. Figure 4.4 presents a notional of the airports and routes served. Note that, with a fixed switching percentage, the routes served were concentrated where the population density is higher.

Table 4.14: Metrics of effectiveness - Experiment 2

Operating Profit ($)	1,671,281
Passengers served	14,713
True Market Share	4.5 %
Number of Routes served	474
Number of Airports served	83

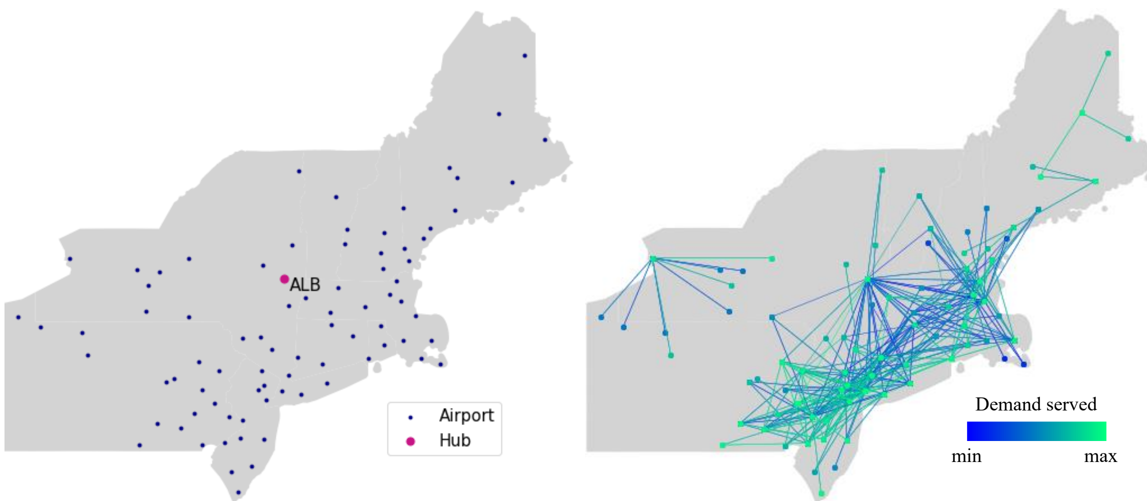


Figure 4.4: Experiment 2 results - *left:* airports served; *right:* routes served

In conclusion, the proposed method was able to perform SD&FA without a baseline schedule, using a notional hourly distribution that can be easily updated, with reduced computational time. Moreover, although the methodology does not consider recapture effects, it can effectively simulate the spill cost by accounting for demand at the itinerary level, keeping a medium level of fidelity. Therefore, the approach described by **HP2** can successfully meet the criteria by providing an alternative methodology to perform SD&FA with medium accuracy. Although it is difficult to make one-to-one comparisons of run time due to the differences in computing power and problem size, authors have reported that their studies typically take many hours or days to run, while this study took a couple of hours for a considerably large potential network using a computer with 16GB RAM and a Windows 64-bit operating system.

4.3 Hypothesis Testing Review

As discussed in section 2.1, **HP1** fails to be rejected if the other alternatives represented by the MNL models and the opportunity cost compared to the income distribution at the itinerary level do not yield satisfactory results based on the established criteria. The experiments detailed in section 4.1 demonstrated that MNL models, if not calibrated, lead to substantially different results and therefore require calibration. The opportunity cost, on the other hand, when applied to the itinerary level and compared to the income distribution, resulted in poor fidelity values of itinerary attractiveness. The methodology described in **HP1** yielded representative values without requiring calibration data, and thus **HP1** was accepted.

HP2 was also accepted since the schedule design and fleet assignment could be successfully performed using a generic distribution. The experiments described in section 4.2 demonstrated that the flow of passengers throughout the day precisely reflected the distribution. In addition, the flight schedule resulted from the adapted ITD&FA was substantially impacted by the hourly trip distribution, as expected.

CHAPTER 5
FRAMEWORK DEMONSTRATION

As detailed in section 2.3, a series of case studies were proposed to demonstrate the capabilities of the methodology, which adopts the approach defined by **HP1** to compute the itinerary attractiveness to support the SD&FA adapted to thin-haul operations defined by **HP2**. These what-if scenarios were conducted to understand how certain operational and performance parameters affect the metrics of effectiveness.

5.1 Network Structure

To understand the impact of the network selection on the effectiveness of thin-haul operations, three types of networks structures were tested using the complete framework described in chapter 3: i) a pure point-to-point network with only non-stop flights; ii) a hub-and-spoke network with only connecting flights; and iii) a hybrid network with both flight types. The potential routes analyzed, as well as the hub location, are depicted in Figure 3.10.

Table 5.1 presents the metrics of effectiveness for the analyzed network structures. The percentage of time saved represents the average among the potential itineraries of a route, regardless of the departure time. As previously mentioned, the total profit represents the value of the objective function without the penalty component. The results demonstrated that the hybrid network presented the most favorable balance between profit, air service expansion, and travel time reduction. Although the hub-and-spoke structure yielded higher values of profit per passenger, this type of network presented the lowest value of operating profit and was capable of serving a limited number of airports and passengers. As expected, the hub-and-spoke network also yielded reduced time savings for travelers, while the point-to-point network presented the highest minimum and maximum percentages of time saved.

Table 5.1: Comparison between network structures

	Hub-and-spoke	**Point-to-point**	**Hybrid**
Operating Profit ($)	190,268	195,861	293,547
True market share	0.55%	0.62%	0.91%
Passengers served	1,826	2,048	2,981
Profit per pax	104.2	95.6	98.5
Routes served	129	85	157
Airports served	30	37	46
Min % of Time saved	33.8%	50%	41.0%
Max % of Time saved	67.1%	81.3%	81.3%
Total number of ATR 42	7	0	2
Total number of P2012	101	175	224

The hybrid network presented intermediate values of time savings between the other two structures. The profit value, on the other hand, increased by 54.3% and 49.8% when compared to the hub-and-spoke and point-to-point networks, respectively. By adopting a hybrid network, airlines could achieve higher profitability, reach more passengers and communities, serve more O&D pairs, and successfully reduce the door-to-door travel time of passengers. Therefore, the thin-haul market can be more effectively served when a mix of point-to-point and connecting flights is adopted by the carrier, balancing the benefits for both airline, passengers, and communities.

In addition to Table 5.1, Figure 5.1 shows the average switching percentage, time saved, and $\Delta Cost/\Delta Time$ of the routes served based on the county-to-county distance for the three types of network. The average $\Delta Cost/\Delta Time$ was determined similarly to the percentage of time saved. The average switching percentage was computed considering the sum of potential passengers across all itineraries of a route divided by its daily ground demand. The bubble size reflects the average percentage of time saved or $\Delta Cost/\Delta Time$ among the routes served.

Figure 5.1 reinforces that a point-to-point network yields higher time savings for passengers, while a hub-and-spoke one presents the lowest values and a hybrid network of-

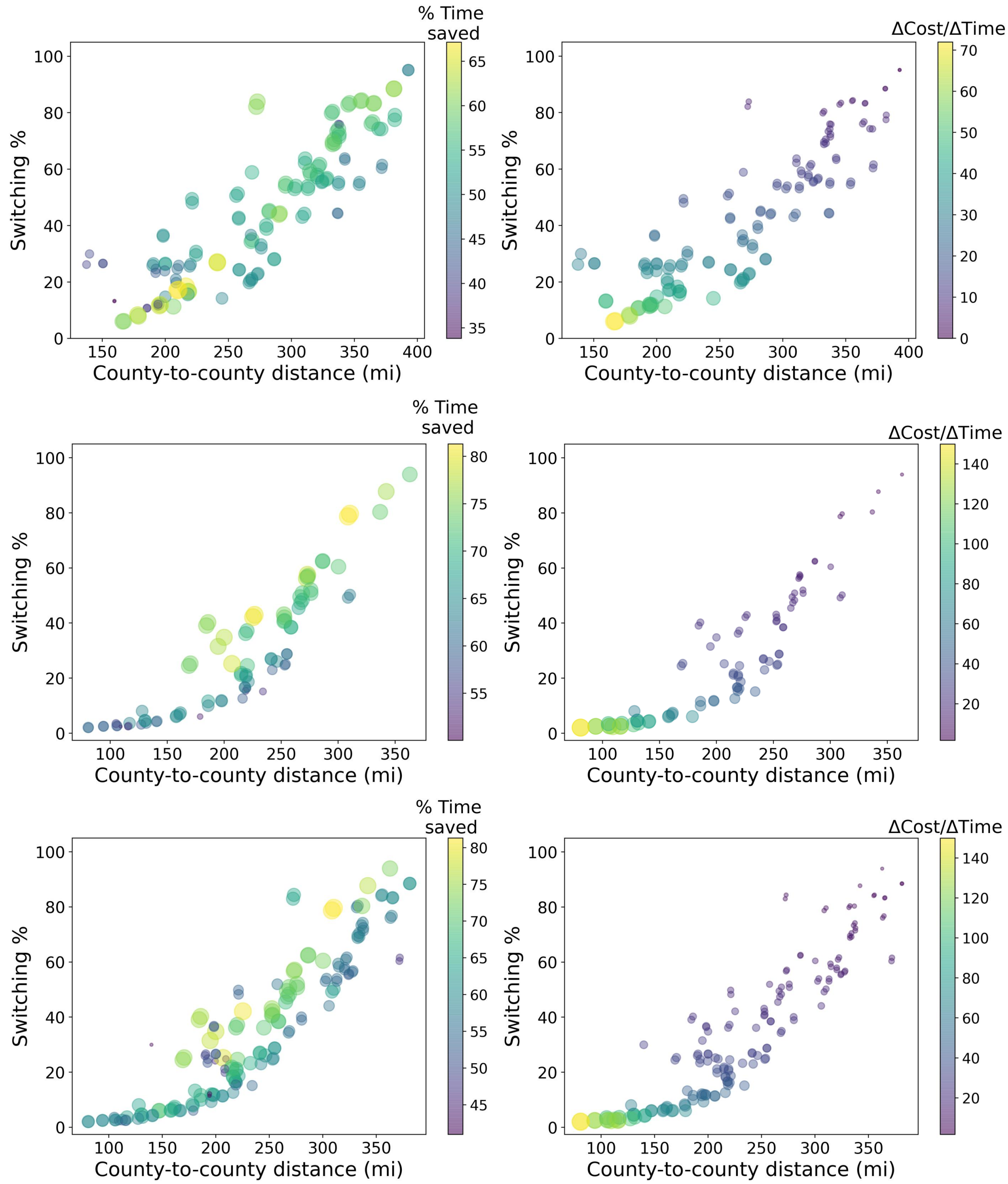


Figure 5.1: Average switching percentage based on time saved (*left*) and $\Delta Cost/\Delta Time$ (right) of routes served - *top:* hub-and-spoke network; *middle:* point-to-point network; *bottom:* hybrid network

fers intermediate results that closely matches the point-to-point ones. Most of the routes served in the hub-and-spoke network presented a percentage of time saved between 40% and 65%, which goes up to 55% to 80% in the hybrid network and between 60% and 80% in the point-to-point one. Figure 5.1 also demonstrates the expected relationship between $\Delta Cost/\Delta Time$ and switching percentage, i.e., lower values of opportunity cost lead to higher switching percentages. In addition, the longer routes presented higher values of $\Delta Time$, resulting in higher switching percentages. Another important observation is that some routes could be profitably served even when presenting small values of switching percentage. Those routes were mostly the ones with high daily ground demand, located in the populated areas of New York and New Jersey.

Furthermore, Figure 5.2 depicts the distribution of routes served and legs flown for each one of the network structures. For the hub-and-spoke network, the served O&D pairs are limited to those around the hub location. The point-to-point network was able to spread the air service to other areas, although serving a lower number of routes. Nonetheless, a significant improvement in the air service distribution was achieved with the hybrid network, with more routes being covered and the air service further spread throughout the states. The concentration of routes around the New York and New Jersey states was influenced by the connection possibilities and the high population density in this coast area.

Thus, the hybrid network scenario was defined as the *baseline* one. The results of this scenario were further expanded in Figure 5.3, which depicts a comparison between the potential and the served routes, as well as between all possible flight legs and the flights that were covered. Most of the served O&D pairs have a county-to-county distance around 200, 250, and 350 miles. The flights covered, on the other hand, presented high frequency close to 150 miles distance.

Among the routes served, the ones over 200 miles were more attractive time-wise to passengers and therefore presented higher switching percentages. The shorter routes served, on the other hand, were possibly the ones with higher daily ground demand that

Figure 5.2: Results of routes served (*left*) and legs flown (*right*) - *top:* hub-and-spoke network; *middle:* point-to-point network; *bottom:* hybrid network

yielded significant potential demand even at small values of switching percentage, as previously mentioned. Note that the flight distances were limited to 225 miles, which is the range of the P2012. For the hybrid electric scenario, 224 P2012 and 2 ATR 42 were employed to daily serve the 2,981 passengers. The ATR 42 were likely used only in the hub connections; with the low-volume characteristic of the routes, the ATR 42 becomes ineffective in non-stop flights. For reference, Cape Air, the largest regional airline in the USA, has a fleet of 88 9-seat Cessna 402s and four 10-seat Britten-Norman Islanders, used to transport over an average of 1,370 passengers daily and serve 37 airports, with more 102 Tecnam P2012 ordered in 2017 [69]. Thus, considering the number of passengers transported daily, the hybrid network required a similar fleet size that Cape Air currently operates.

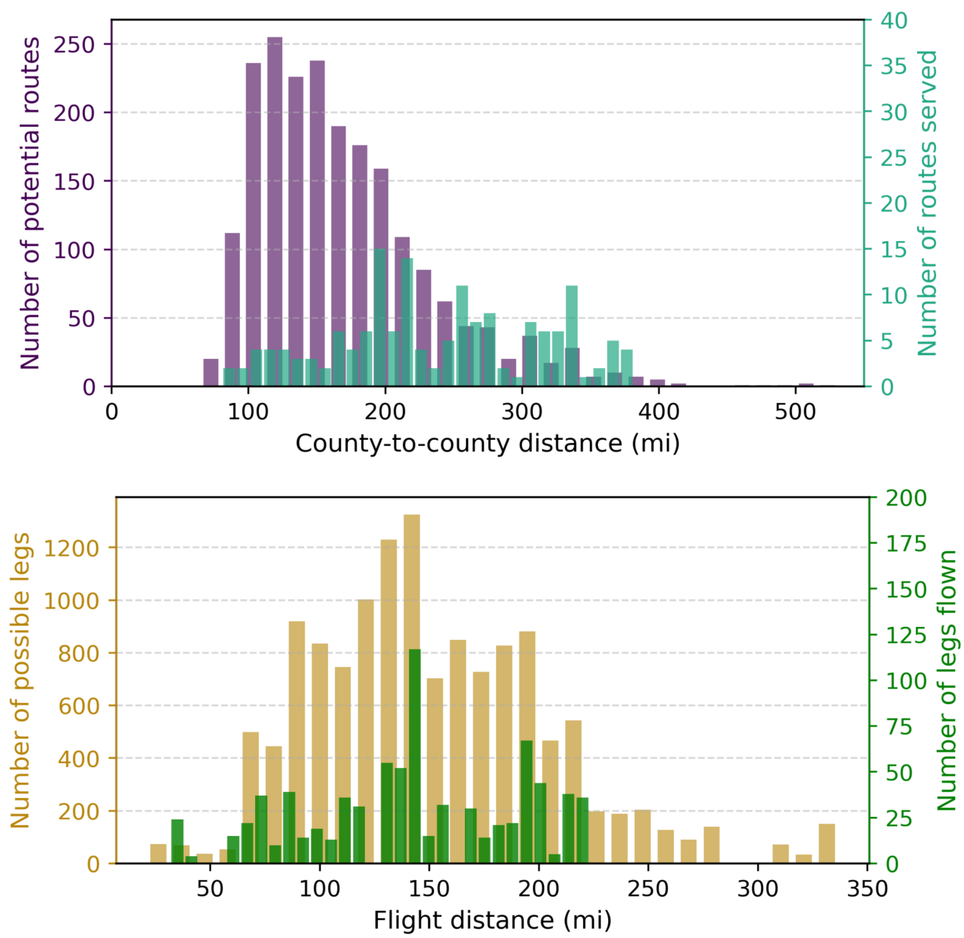


Figure 5.3: Hybrid network results: *top:* distribution of routes by distance; *bottom:* distribution of flights by distance

Moreover, Figure 5.4 presents the cumulative potential demand of the routes served and the passengers transported. The routes were grouped by 10-mile segments. The potential demand and the total number of passengers transported in a day across all itineraries were added for each group. Potential demand in this case represents the daily ground demand multiplied by the switching percentage. Most of the potential demand and the passengers transported were concentrated in routes between 250 and 350 miles, which reflects the higher levels of switching percentages of these routes. The histogram also demonstrates that the potential market share and the true market share can be significantly different. For the hybrid network, the average potential market share across all routes was approximately 8.4%, against a true market share of 0.91%. Only about 11% of the potential demand was captured. Among the routes served, the potential market share dropped to 2.1%, in which around 42% was served, as depicted in Figure 5.4. In contrast, the hub-and-spoke network presented a potential market share of 3.35% due to the lower attractiveness of the routes. The true market share was limited to 0.55% as shown in Table 5.1, and among the routes served, the potential market share reduced to 1.6%, in which only about 35% was served.

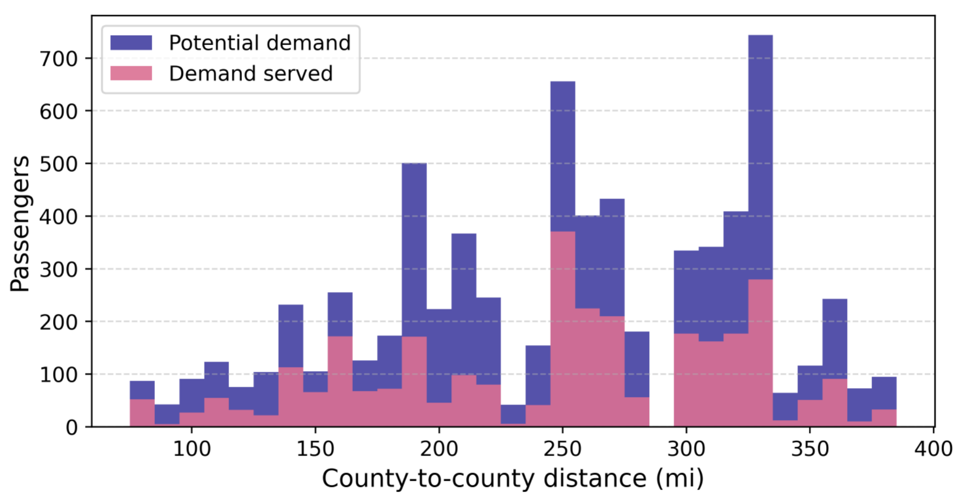


Figure 5.4: Distribution of passengers transported in a hybrid network

5.2 Longer Aircraft Range

One of the main limitations of using electric propulsion systems is the reduced range of the aircraft. The limited range of the 9-seat P2012 might be the reason thin-haul operations could not reach some of the routes in the potential network. On the other hand, despite the longer range of the ATR 42, this aircraft has a seat capacity incompatible with most of the flight demand. Nonetheless, these aircraft models were developed as a retrofit, in which the propulsion system was replaced without any other design changes. If a complete design is performed considering an electric propulsion system, the vehicles would be fully optimized, with potential enhancements in the performance parameters.

Current developments in the industry have culminated in new fully electric and hybrid-electric aircraft designs with significant improvements in the design range. One example is the Alice aircraft developed by the Eviation company, a 9-seat fully electric vehicle with design range of 440 nmi, or approximately 500 miles, and cruise speed of 250 mph [70]. Another recent design is the 12-seat hybrid-electric vehicle developed by Zunum Aero with design range of 700 miles and cruise speed of 340 mph [71]. Based on these new aircraft developments, an hypothetical scenario considering the electric P2012 with a longer range of 500 miles, equivalent to the Alice aircraft, was analyzed for the hybrid network.

Table 5.2 shows the results compared against the baseline scenario. Employing aircraft with longer range substantially increased the operating profit by 54.2% and the number of passengers served. This occurred mainly because the longer range allowed more non-stop itineraries to be covered. It also increased the possibility of flight connections. For instance, Figure 5.5 shows that more routes connecting Pennsylvania state became feasible when compared to the baseline scenario depicted in Figure 5.2, with more airports in this state receiving air service, as depicted in Figure 5.6. The number of airports served, on the other hand, remained roughly the same, suggesting that the air service was transferred to routes with higher demand that were not feasible with the shorter-range aircraft.

Table 5.2: Longer range scenario results

	Baseline	Longer range
Profit ($)	293,547	452,681
True market share	0.91%	1.51%
Passengers served	2,981	4,976
Routes served	157	166
Airports served	46	49
Minimum % of Time saved	41.0%	41.0%
Maximum % of Time saved	81.3%	81.3%
Number of ATR 42	2	0
Number of P2012	224	362

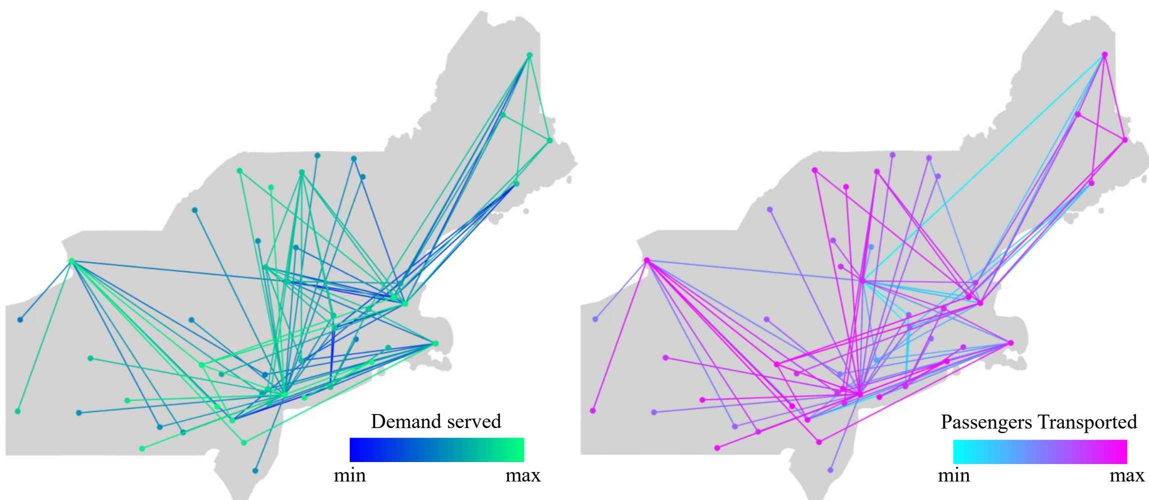


Figure 5.5: Routes served (*left*) and flights covered (*right*) when adoption an aircraft with longer range

The experiment also demonstrated that the low-volume demand and the unattractive opportunity cost of many potential routes cannot be overcome even when non-stop itineraries or more connection opportunities are available. Nonetheless, Figure 5.5 shows that the air service was more evenly distributed throughout the Northeastern states when the longer-range aircraft was employed.

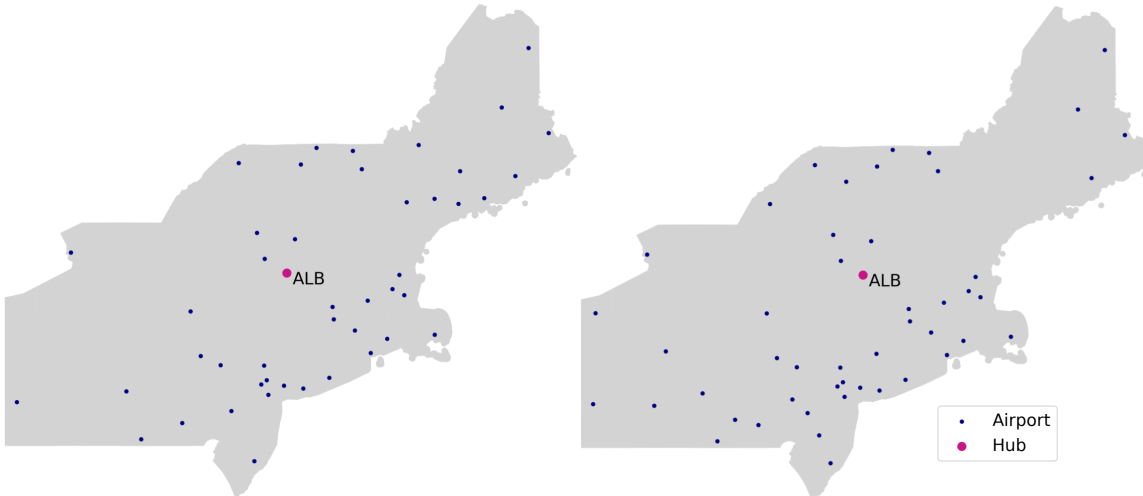


Figure 5.6: Airports served - *left:* baseline scenario; *right:* longer range scenario

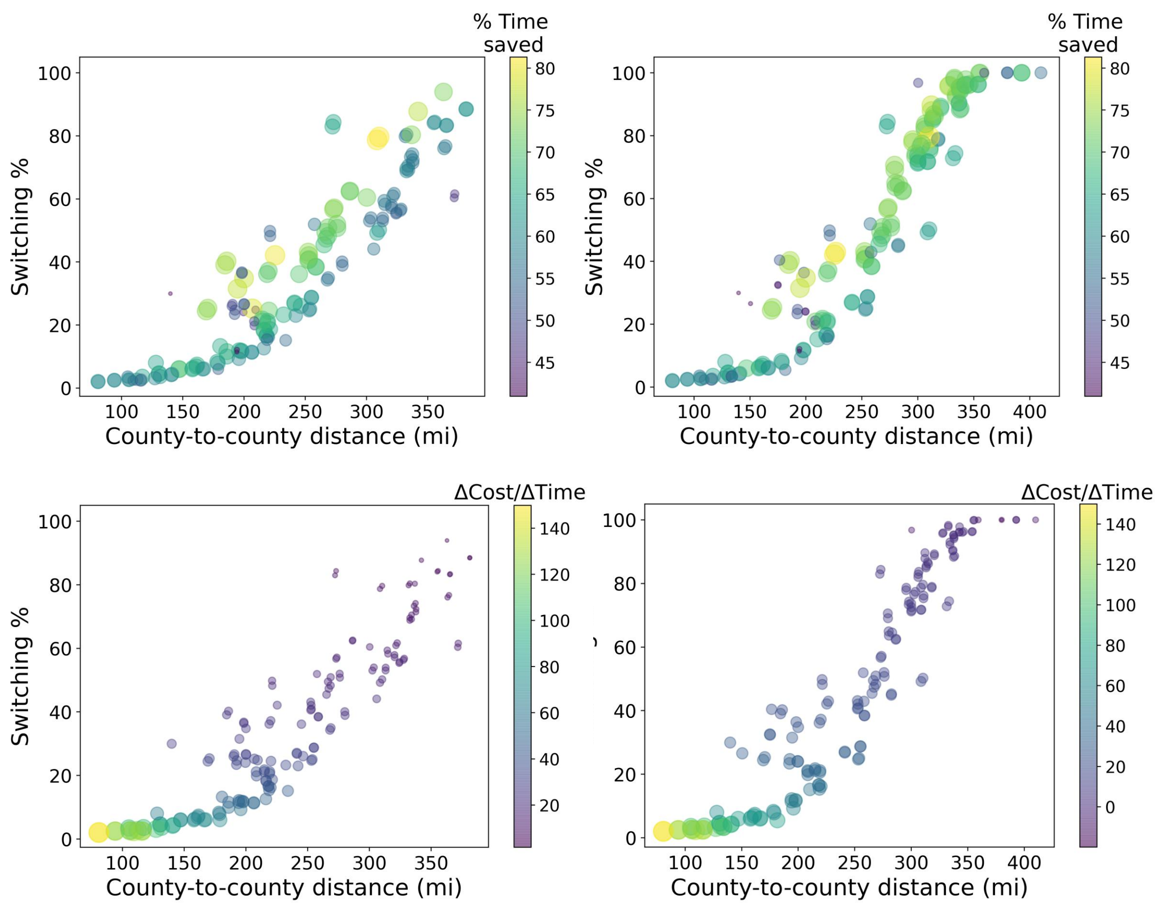


Figure 5.7: Average switching percentage based on time saved (*top*) and opportunity cost (*bottom*) of routes served - *left:* baseline scenario; *right:* longer range scenario

Figure 5.7 above depicts the scenario results for the switching percentage based on the average values of percentage of time saved and opportunity cost. The minimum and maximum percentages of time saved remained the same. The average values, however, increased for longer range routes due to the existence of non-stop itineraries, which were not allowed in the baseline scenario. Furthermore, some routes now achieved a switching percentage of 100%, with some of them presenting a negative value of opportunity cost. This occurs when the fare, and the overall cost of air service, is cheaper than the driving cost, which can occur in longer routes.

In addition, Figure 5.8 supports that longer routes benefited from the greater aircraft range. Most of the served O&D pairs present county-to-county distance between 300 and

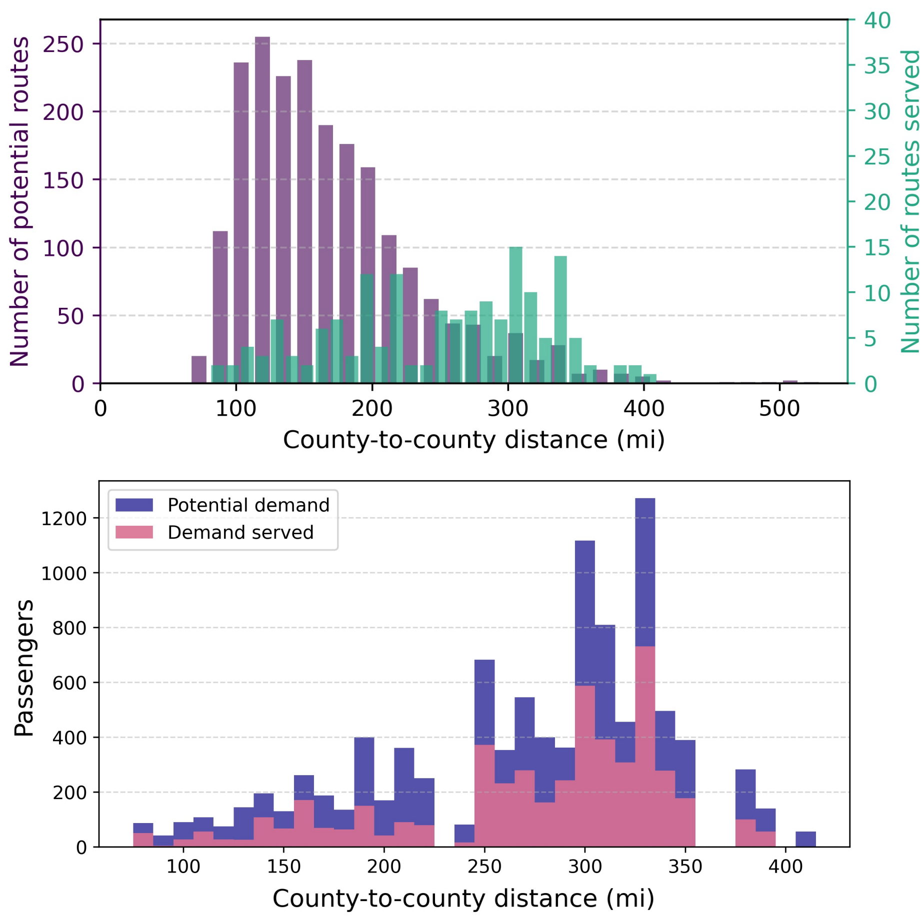


Figure 5.8: Distribution of routes served (*top*), and passengers transported (*bottom*) when using an aircraft type with longer range

350 miles. These routes also concentrate the majority of passengers transported, reinforcing that the longer-range aircraft allowed the service to reach routes that were not feasible but could present substantial demand. Nonetheless, the significant increase in the number of passengers transported required a larger number of aircraft, with a fleet of 362 P2012.

5.3 Average Aircraft Speed

Propeller-driven small capacity aircraft have cruise speeds considerably lower than large capacity, jet engine aircraft. Because the aircraft speed directly affects passenger travel time, a sensitivity analysis was conducted considering two different assumptions for the average aircraft speed. The first case adopted an aircraft speed of 185 mph, lower than the baseline scenario, based on the average between the climb and cruise speeds of a retrofitted P2012 designed by Justin et al. [7]. On the other hand, since advanced 6 to 10-seat aircraft are expected to reach a cruise speed of 375 mph [18], the second case assumed an average speed of 300 mph, also based on the cruise speed of recent electric aircraft designs [70, 71]

Table 5.3 shows the results for the two cases and the baseline scenario. As expected, a higher aircraft speed led to improvements in the operating profit while serving more routes and airports and transporting more passengers, and the opposite occurred for a lower speed. Similarly to the longer aircraft range scenario, the operations required more aircraft to accommodate the increase in passengers transported, and vice-versa.

In addition, the minimum and maximum percentages of time saved experienced by passengers accordingly reflect the changes in speed. As expected, a higher average speed increased the $\Delta Time$ of the itineraries, lowering the opportunity cost of the potential O&D pairs and amplifying the number of routes with switching percentage and demand significant enough to yield profitable operations. The opposite occurred with the lower average speed. Figure 5.9 depicts this trend.

Table 5.3: Results of different average speed assumptions

	Lower speed	**Baseline**	**Higher speed**
	185 mph	250 mph	300 mph
Profit ($)	192,794	293,547	361,561
True market share	0.61%	0.91%	1.13%
Passengers served	2,019	2,981	3,708
Profit per pax	95.5	98.5	97.5
Routes served	113	157	188
Airports served	36	46	53
Minimum % of Time saved	34.3%	41.0%	37.0%
Maximum % of Time saved	77.1%	81.3%	83.1%
Number of ATR 42	0	2	5
Number of P2012	163	224	265

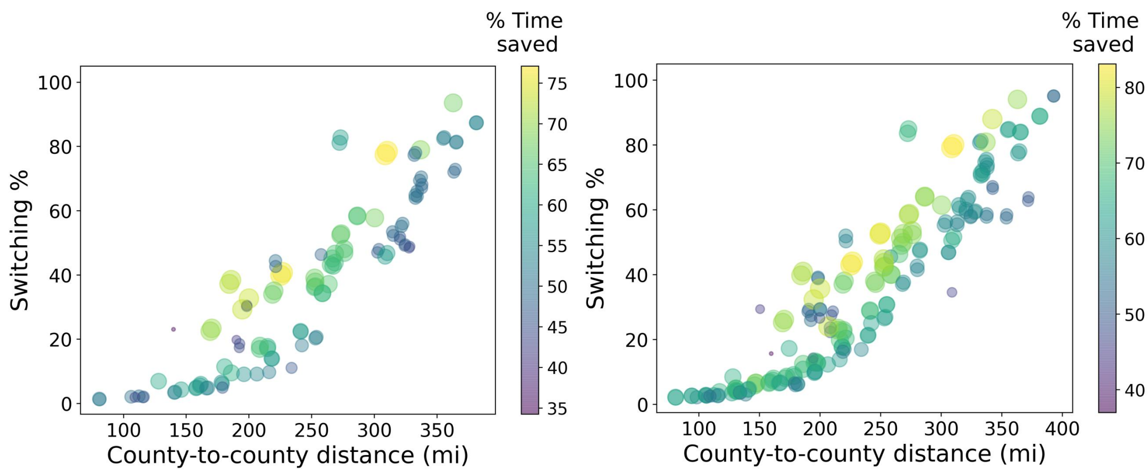


Figure 5.9: Average switching percentage based on time saved - *left:* lower speed; and *right:* higher speed

Furthermore, Figure 5.10 shows the increase in number of routes and airports served in the Northeastern regions with the increase in aircraft speed. When compared to the baseline scenario, the airports in New Jersey and Pennsylvania were the most benefited by the employment of faster aircraft. The use of lower-speed aircraft, on the other hand, practically precluded the air service expansion in the Pennsylvania area.

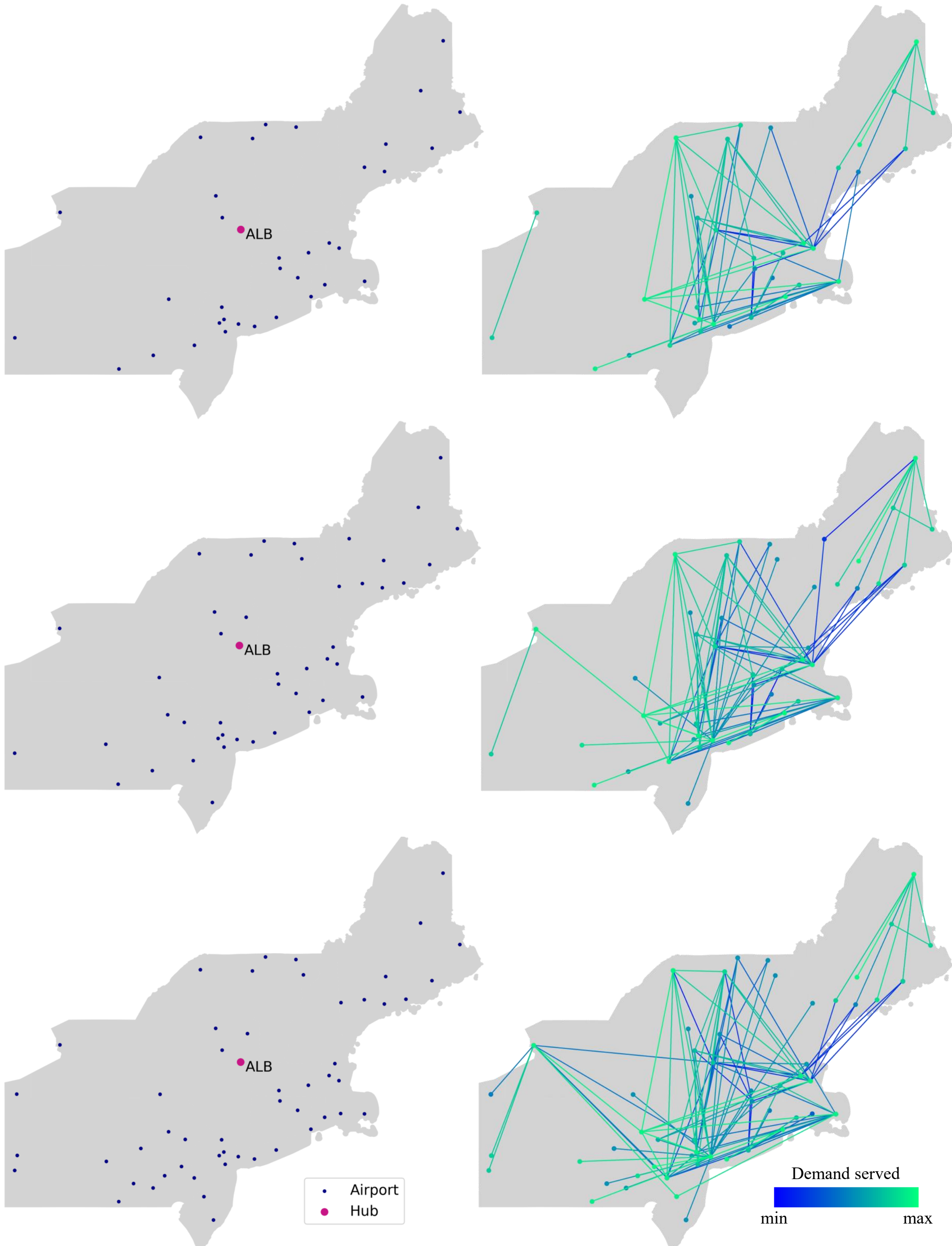


Figure 5.10: Airports (*left*) and routes served (*right*) - *top:* lower speed; *middle:* baseline scenario; *bottom:* higher speed

5.4 Different Hub Locations

Another operation decision that could potentially impact the effectiveness of the air service is the hub location. Two additional scenarios were analyzed considering different airports as hubs: one at Wilkes-Barre Wyoming Valley Airport (WBW), PA, and a second scenario with a hub at Eastern Slope Regional Airport (IZG), ME, as depicted in Figure 5.11. The scenarios were studied under both hub-an-spoke and hybrid networks, since different hub locations could improve the effectiveness of the hub-and-spoke structure as well.

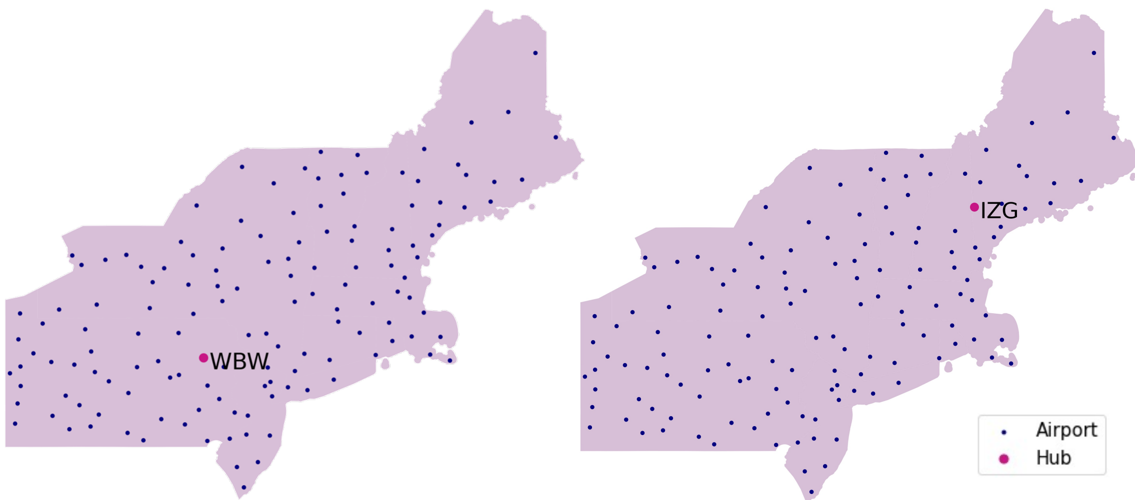


Figure 5.11: Potential network structure with different hub locations

Table 5.4 provides the results for the hybrid network and the hub-and-spoke network for both hub locations. The results followed the same trend of the experiment conducted in section 5.1, with the hybrid network being the most effective network structure in both cases. The location of the hub, however, highly impacted the metrics of effectiveness, especially for the hub-and-spoke network. In this case, placing the hub at Albany International Airport, in the central region of Northeastern states, led to considerably higher profitability and demand served for both hybrid and hub-and-spoke network structures, as demonstrated by the baseline scenario results.

In addition, Figure 5.12 and Figure 5.13 depict the distribution of routes served and flights covered in both scenarios. As expected, the coverage of the hybrid network was much broader in both cases. The flights and airports served in the hub-and-spoke network remained concentrated around the hub location.

Table 5.4: Comparison between hybrid and hub-and-spoke network for different hub locations

	Baseline (ALB)		WBW		IZG	
	HS[1]	**Hybrid**	**HS**[1]	**Hybrid**	**HS**[1]	**Hybrid**
Profit ($)	190,268	293,547	65,671	231,882	64,421	229,762
True market share	0.55%	0.91%	0.18%	0.72%	0.23%	0.75%
Passengers served	1,826	2,981	599	2,372	750	2,485
Profit per pax	104.2	98.5	109.6	97.8	85.9	92.5
Routes served	129	157	44	112	82	122
Airports served	30	37	15	43	17	44
Minimum % of Time saved	33.8%	41.0%	36.8%	42.8%	30.9%	36.1%
Maximum % of Time saved	67.1%	81.3%	71.4%	81.3%	62.4%	81.3%
Number of ATR 42	7	2	0	0	0	0
Number of P2012	101	224	32	185	51	203

[1] Hub-and-spoke

Furthermore, Figure 5.14 and Figure 5.15 show the distribution of potential demand and passengers transported among the routes served for the hub located at WBW airport and at IZG airport, respectively. In the first scenario, the average potential market shares were 7.8% and 2.2% for the hybrid network and the hub-and-spoke network, with the true market shares being 0.72% and 0.18%, respectively. The hybrid network in this case was able to capture 9.2% of its potential market, while the hub-and-spoke network reached 8.1% of its market. These values increase to 42% and 26% if only the routes served are considered. In the second scenario, with the IZG airport as hub, the potential market shares were about 7.7% and 1.6% for the hybrid and hub-and-spoke networks, respectively. The true market shares were equivalent to 0.23% and 0.75%, in which case the hybrid network could serve 9.8% of its potential market, and the hub-and-spoke 14.2%. Once again, these values increase to 43.4% and 24.8% if only the routes served are considered. The hybrid network, therefore, was able to capture more passengers among the routes served. The hub-and-spoke network was able to capture more of its potential market share in general, although the potential demand was considerably lower and the effectiveness of this network structure among the routes served was limited.

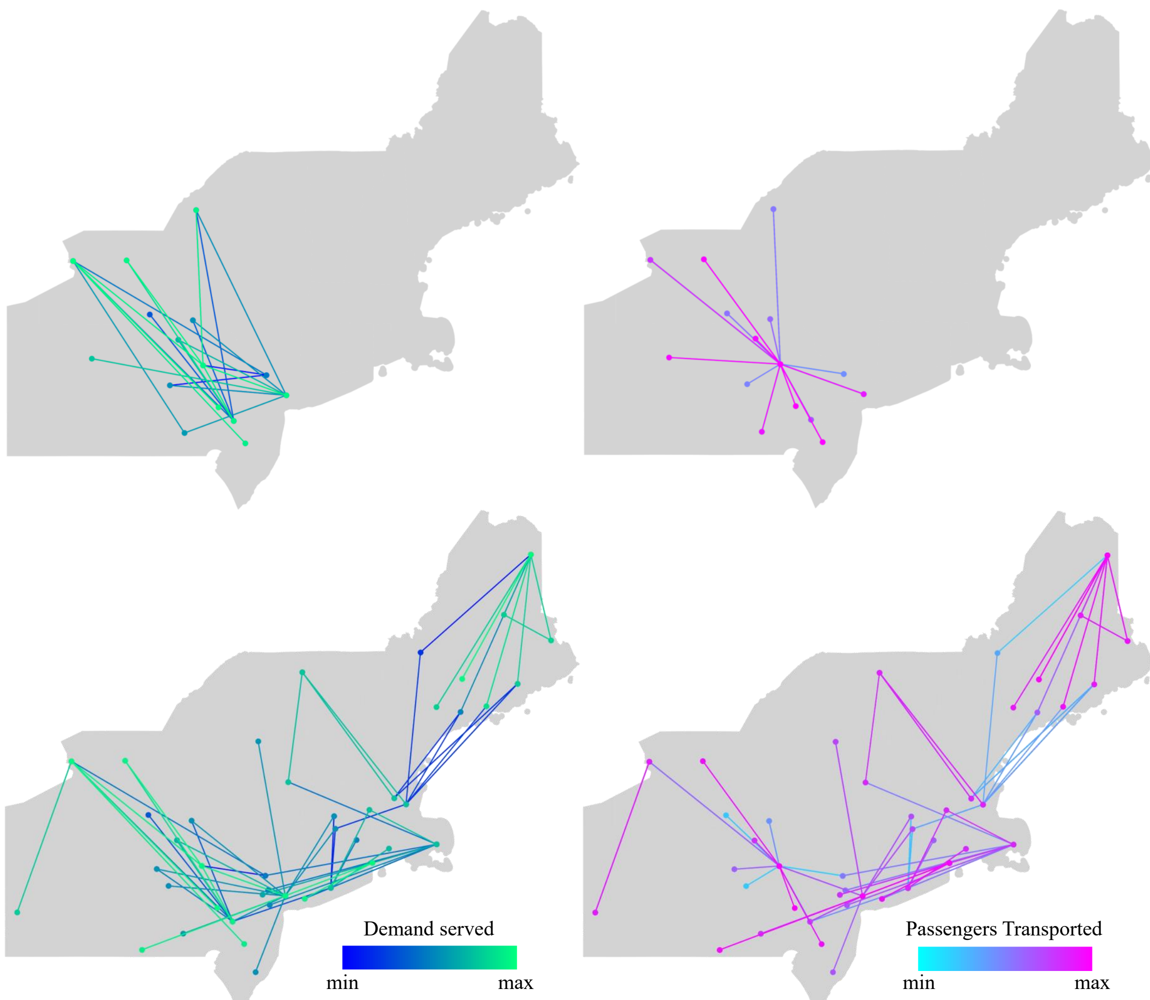


Figure 5.12: Routes served (*left*) and flights covered (*right*) for hub located at WBW - *top:* hub-and-spoke network; *bottom:* hybrid network

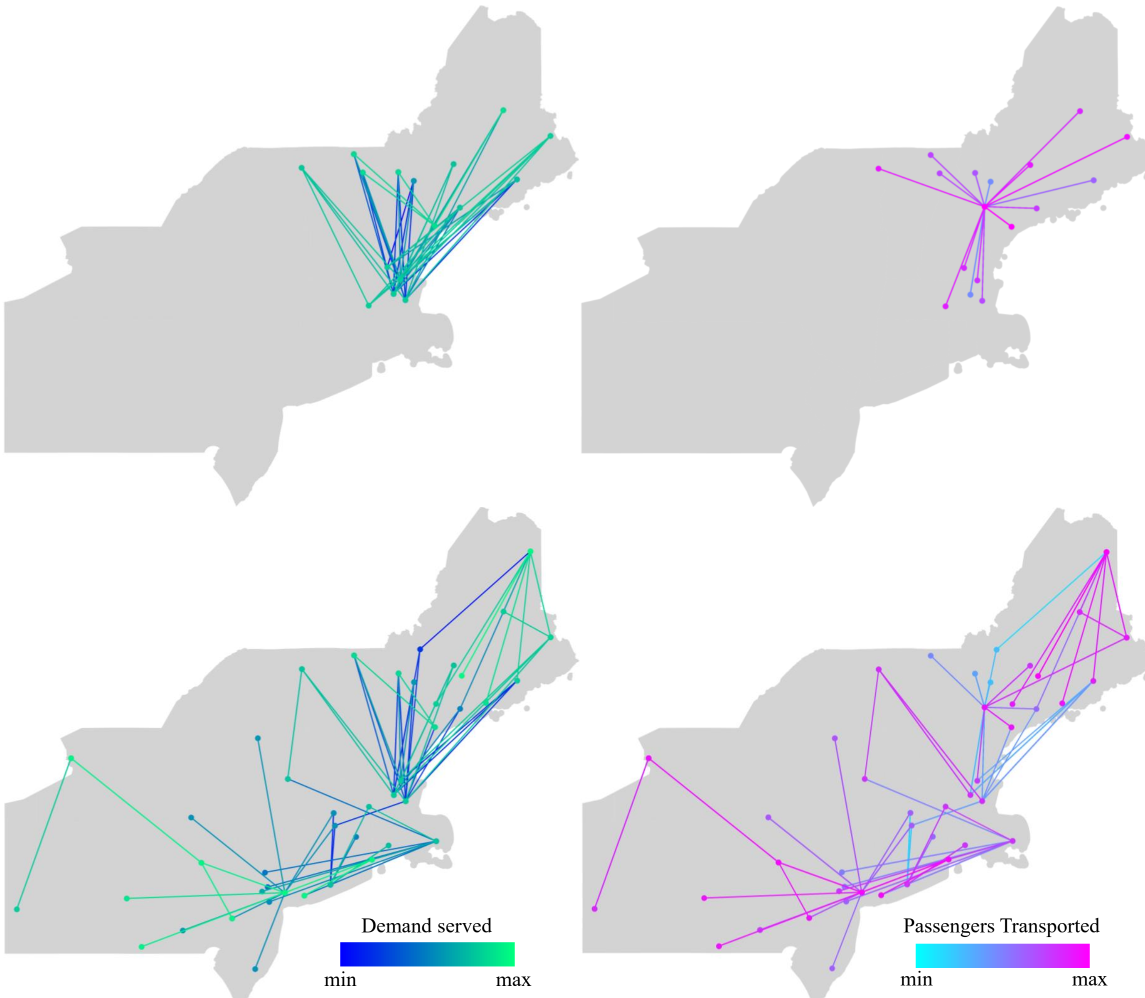


Figure 5.13: Routes served (*left*) and flights covered (*right*) for hub located at IZG - *top:* hub-and-spoke network; *bottom:* hybrid network

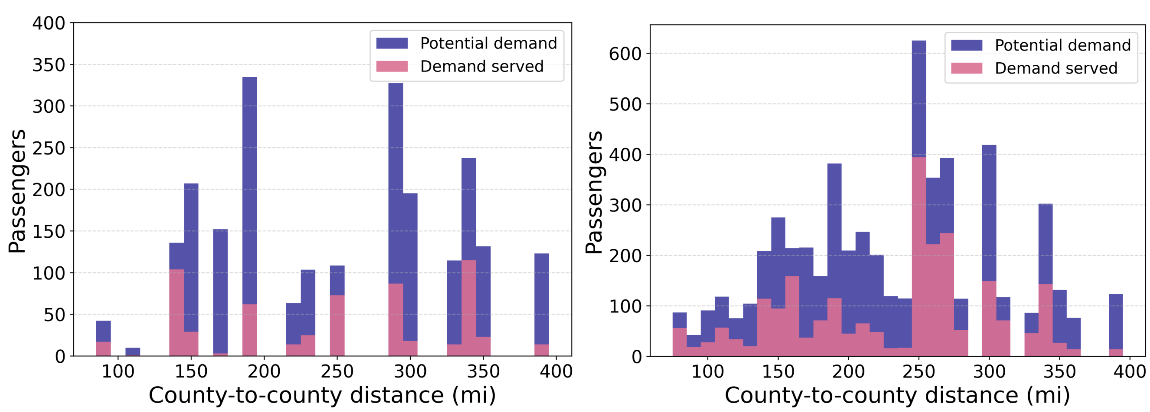


Figure 5.14: Distribution of potential demand and passengers transported of routes served for hub located at WBW - *left:* hub-and-spoke network; *right:* hybrid network

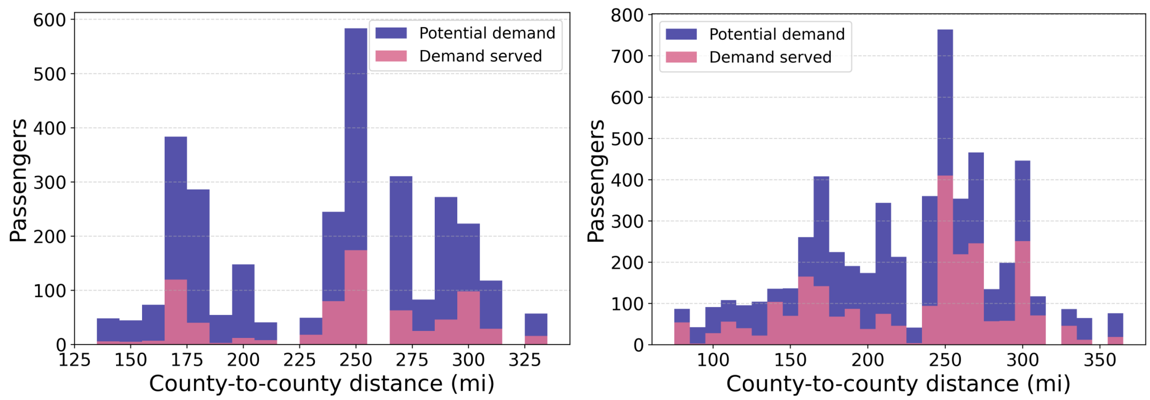


Figure 5.15: Distribution of potential demand and passengers transported of routes served for hub located at IZG - *left:* hub-and-spoke network; *right:* hybrid network

An additional scenario was analyzed considering a potential network with both WBW and IZG as hubs. Table 5.5 shows an improvement in most of the metrics for both networks, especially in the profit, passengers transported, and number of routes and airports served. The minimum and maximum percentage of time savings remained the same.

Table 5.5: Results for a network with two hubs

	WBW		IZG		WBW-IZG	
	HS[1]	Hybrid	HS[1]	Hybrid	HS[1]	Hybrid
Profit ($)	65,671	231,882	64,421	229,762	130,093	266,717
True market share	0.18%	0.72%	0.23%	0.75%	0.41%	0.86%
Passengers served	599	2,372	750	2,485	1,349	2,830
Profit per pax	109.6	97.8	85.9	92.5	96.4	94.2
Routes served	44	112	82	122	126	151
Airports served	15	43	17	44	32	50
Minimum % of Time saved	36.8%	42.8%	30.9%	36.1%	30.9%	36.1%
Maximum % of Time saved	71.4%	81.3%	62.4%	81.3%	71.4%	81.3%
Total Number of ATR 42	0	0	0	0	0	0
Total Number of P2012	32	185	51	203	83	215

[1] Hub-and-spoke

Adopting two hubs had a greater impact in the hub-and-spoke network, with substantial improvements in the air service expansion, as depicted in Figure 5.16. A network with one central hub at Albany, however, was still more effective for both network structures analyzed. Therefore, location and number of hubs in the network are two relevant decisions that substantially affect the overall effectiveness of the operations. These decisions also depend on airport infrastructure and capacity, potential costs, government incentives, and other logistics and cost-related aspects. Nonetheless, the majority of airlines established one hub as the center of their operations.

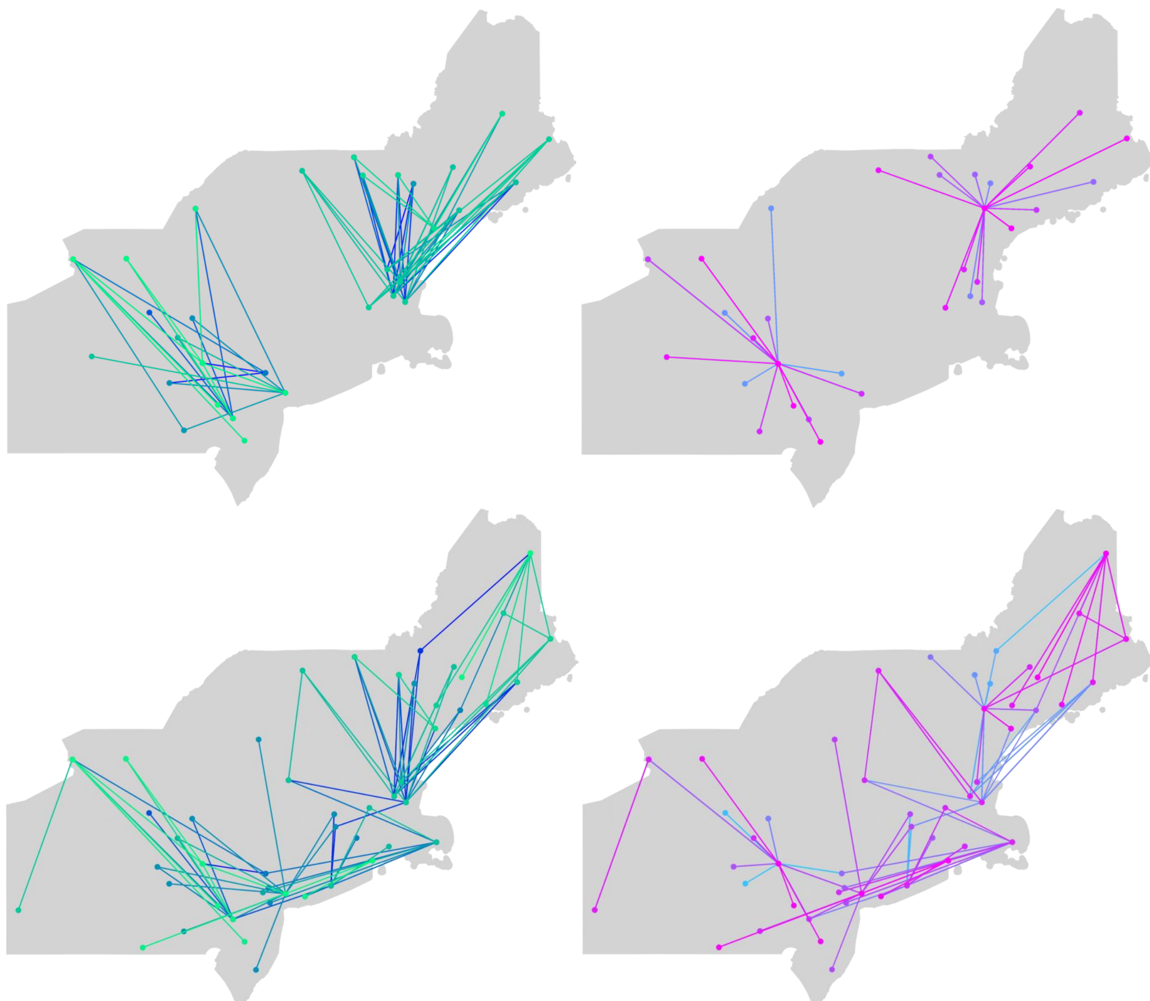


Figure 5.16: Routes served (*left*) and flights covered (*right*) for two hubs located at WBW and IZG - *top:* hub-and-spoke network; *bottom:* hybrid network

5.5 Discussion

As stated by the *overarching hypothesis*, the proposed methodology provides *a comprehensive assessment of the economic viability of thin-haul operations that integrates thin-haul scheduled demand estimation methods with SD&FA techniques to account for the true market share and multiple concepts of operations considering the competition with alternative modes of transport*. The experiments in section 5.1 demonstrated that the methodology can successfully determine the routes that can be profitable served and the true market share. As indicated, the true market share differs significantly from the potential market share, which is the focus of the majority of the studies in the literature. Thus, determining only the potential demand may yield equivocal observations regarding the possibility of establishing thin-haul scheduled operations. This supports one of the main claims in this thesis, that this proposed methodology is more suitable for analyzing the viability of thin-haul operations from the airline perspective when compared to the other studies in the literature.

Furthermore, the experiments performed in section 5.1 demonstrated that the frameworks allows the assessment of the most efficient CONOPs to serve the thin-haul market for different scenarios. The results indicated that the adoption of a hybrid network structure yields more efficient thin-haul operations. This network structure achieved the best balance between profit, air service expansion, and door-to-door travel time reduction. Additional experiments with different hub locations indicated the hybrid network was still more effective under other circumstances. Further sensitivity studies were performed to investigate the impact of employing a fleet with performance enhancements. The results demonstrated that longer-range aircraft have the greater potential to improve the overall effectiveness of the operations due to the increase in possible non-stop flights and connections.

One important observation is that some regions are unlikely to be candidates to receive air service in the future even with the projected improvements in aircraft performance enabled by advanced technologies. The most probable reason is the ultra-low demand. Even with high switching percentage, if the daily demand is too low, it becomes practically negligible when scattered throughout the day considering different departure times. Another observation regards the low employment of ATR 42s, which does not surpass seven aircraft even in the hub-and-spoke network. Since the 48-seat aircraft appears to be inadequate for the scenarios presented, its replacement by a typical 19-seat aircraft often employed by commuter airlines could potentially improve the effectiveness of the operations. These type of studies allow airlines to understand the operations decisions necessary to serve the thin-haul market more efficiently, therefore answering **RQ3**.

Some assumptions in this thesis were established considering that thin-haul passengers would have easy access to airports, with no need for a full security protocol [10]. Allied with simplified check-in, the boarding process should be considerably faster. In addition, the short connection of 30 minutes was assumed considering that changing airplanes would take a brief time for small and regional airports. These two assumptions, however, might be unrealistic for larger airports such as LaGuardia or Boston Logan. A more detailed analysis for the airport categories should be considered, including the assessment of infrastructure conditions. Nonetheless, these larger airports were still accounted since a considerable amount of passengers that originate from small communities have main metropolises as destinations. Besides, business and leisure travelers were combined and treated as one passenger class; in fact, passengers with different trip purposes have different travel behaviors that should be considered in order to achieve more representative results.

Lastly, in the absence of recent surveys, the Traveler Analysis Framework used as demand input was constructed retrieving data from the ATS and NHTS surveys. These surveys, however, were conducted in 1995 and 2001 and might not reflect recent changes in travel patterns. A more recent database, as well as a more accurate hourly trip distribution, should be investigated to obtain more accurate estimates. The proposed methodology can easily accommodate these changes, since it allows the investigation of operations viability under different circumstances.

CHAPTER 6
CONCLUSION

The research objective of this thesis was *to investigate the economic viability of thin-haul operations by developing a framework that accounts for passenger demand and integrated airline schedule design and fleet assignment.* Such framework was build upon the methodology proposed in this thesis to address the research objective, that was decomposed into the following research questions:

> **Research Question 1:** *How can passenger demand be accounted for to support thin-haul operations decisions?*
>
> **Research Question 2:** *How can schedule design and fleet assignment be performed for thin-haul operations?*
>
> **Research Question 3:** *How can the concept of operations to effectively serve the thin-haul market be determined?*

All three research questions have been answered throughout this thesis. The first one was addressed by developing a method for passenger demand at the itinerary level to support SD&FA problems accounting for the competition between air service and ground transport in the thin-haul market. This approach was developed by combining two methods widely adopted in the literature that determine mode split and itinerary choice: opportunity cost and MNL models. As stated by **HP1**, *if choice of mode and itinerary attractiveness techniques are combined, while accounting for competition with alternative modes of transport, then thin-haul passenger demand at the itinerary-level can be quantified with medium fidelity*. The goal was to address the drawbacks of these two methods, namely the low fidelity for itinerary choice applications and the need for massive data for calibration. To do so, first the mode split was computed at the itinerary level using the opportunity cost. The mode split was then integrated to a one-parameter MNL model that does not require calibration to determine the *itinerary attractiveness*. In this methodology, trip time, trip cost, and socioeconomic factors were the attributes considered, since it has been proven that these aspects drive passengers' decision in the thin-haul market. The result was an approach to determine itinerary choice to support SD&FA applied to thin-haul operations with medium fidelity and without requiring data for calibration.

To validate **HP1**, the experiments suggested to compare the results from the MNL models, the opportunity cost approach, and the method proposed in this thesis, as described in section 2.1. The test results in section 4.1 demonstrated that, unlike the two approaches from the literature, the proposed methodology can successfully determine: i) the mode split of the potential routes and the itinerary attractiveness, that represents the itinerary choice of each one of the available itineraries; ii) representative values of itinerary attractiveness without requiring any data for calibration while accounting for the three main aspects that impact passenger choice in the thin-haul market. Therefore, experiments showed that the proposed method presents the most favorable results when compared to the other two models adopted, substantiating **HP1**. Further experiments testing the framework also demonstrated that the method can successfully support SD&FA problems.

The second research question was answered by adapting and addressing the drawbacks of the integrated timetabling development and fleet assignment (ITD-FA) model developed by Wei et al. [47]. This is one of the few authors that performed SD&FA without a baseline schedule, one of the main requirements for thin-haul operations due to the lack of historical aviation data for this market. Nonetheless, the ITD-FA model relies on detailed passenger preference for departure time to perform the SD&FA. This passenger preference model is also built upon historical data from aviation bookings. To circumvent that, **HP2** proposes that *current ITD-FA models can be adapted to support thin-haul scheduling decisions if the relationship between hourly demand distribution and flight schedule is captured considering the competition with alternative modes of transport.* The ITD-FA model was then adapted to capture the hourly distribution of trips covered by passengers using an alternative mode of transport. In this context, schedule decisions are made by accounting for the competition with ground transportation, aiming to capture the passengers that currently use these modes to cover short-range routes.

Other limitations of the ITD-FA model were addressed by the proposed methodology, such as limiting the demand at the itinerary level to prevent passengers from switching to itineraries they may not be able to afford. In this way, itineraries with limited demand can be disregarded, reducing the domain and the computational expense of the problem. This also allows the attractiveness attributes to be decoupled from the hourly distribution, granting more flexibility to the methodology by allowing different trip patterns to be easily investigated, which was another limitation of the ITD-FA model. The experiments proposed in section 2.2 demonstrated that the SD&FA can be successfully performed using an hourly trip distribution with reduced computational time, and that the resultant schedule closely follows this distribution. The test results in section 4.2 showed that, unlike the SD&FA models adopted in the literature, the proposed method in this thesis can: i) perform SD&FA without a baseline schedule; ii) determine the schedule based on the hourly trip distribution from alternative modes of transport and thus account for the competition with alternative modes of transport; iii) provide the flexible approach with reduced computational time required by a decision-making framework.

The last research question was addressed by integrating the aforementioned methods used to answer **RQ1** and **RQ2**, resulting in the proposed methodology in this thesis. The result was a *decision-making* framework that allows the effectiveness of thin-haul scheduled operations to be evaluated under different scenarios and therefore determine the most efficient concept of operations. Unlike other studies, this proposed methodology provides *a comprehensive assessment of the economic viability of thin-haul scheduled operations that integrates thin-haul demand estimation methods with SD&FA techniques to account for the true market share and multiple concepts of operations considering the competition with alternative modes of transport*. The experiments proposed in section 2.3 demonstrated that the framework can successfully determine the profitable routes and the true market share, that differs significantly from the potential market. In this case, the test results indicated that just determining the potential thin-haul market share is not enough to understand if airlines can establish profitable operations over short-range, low-volume routes. The proposed methodology tackled this gap and therefore is more appropriate to investigate the thin-haul market from the airline perspective under different operations scenarios.

In conclusion, the proposed methodology successfully addressed the research objective. Both **HP1** and **HP2** were substantiated and accepted. The hypotheses and the proposed experiments were detailed in chapter 2. The methodology was described in chapter 3 along with the details of the framework implementation, main assumptions, and data adopted in the analyses. Chapter 4 and 5 presented the results of the experiments and the framework demonstration.

6.1 Contributions

The main contribution of this thesis is a methodology that enables the investigation of the viability of thin-haul operations under different scenarios, focusing on the airline operations and economics perspective. The proposed approach successfully overcomes the challenges faced by airlines wishing to serve the thin-haul market, regarding mainly the lack of aviation historical data and airline previous schedule. With the method described in this thesis, demand assessment and integrated schedule design and fleet assignment applied to thin-haul operations can be performed considering the particularities of the market and the challenges aforementioned.

A thorough review of the relevant literature reveals that the approach described in this thesis is the first to tackle thin-haul demand estimation at the itinerary level and SD&FA for this type of operations, providing a comprehensive assessment of thin-haul scheduled operations. The proposed methodology can determine not only the potential market share, but the portion of the prospective demand that can be effectively captured by a carrier. It also allows the assessment of the air service capability to reduce the door-to-door travel time of passengers, which is one of the main goals behind revitalizing the thin-haul market.

The methodology enables stakeholders to understand the key elements that lead to profitable thin-haul operations, the extent to which the air service can be expanded, and the potential benefits for passengers and cities. In addition to the airline operations decisions, this analysis can allow governments to plan future investments and policy incentives. Airports can project future need for infrastructure development and potential increase in air traffic. It also demonstrates the need for investments in future commuter aircraft technologies by manufacturers, especially regarding electric propulsion developments.

6.2 Future Work

The adapted ITD-FA model can be further enhanced to account for passenger recapture between itineraries. In such case, the recapture analysis must consider the fact that passengers cannot freely switch among itineraries; it will depend on their willingness to pay for a more expensive option.

Moreover, the itinerary attractiveness is computed considering the available itineraries. However, if after the performance of the SD&FA some itineraries are no longer available, the attractiveness should be recalculated, followed by the SD&FA optimization in a iterative process until a convergence criterion is reached. The SD&FA problem could also be enhanced to determine the optimum location of the hub.

In addition to the improvements in the assumptions and inputs described in section 5.5, the county-to-county highway distance can be refined considering multiple trips departing from and arriving at different locations within the counties. The same could be extended to the county-airport distance. Traffic congestion studies could also be accounted for, increasing the fidelity of the time savings computation and the demand analysis. All these additional considerations have the potential to enhance the methodology and increase the fidelity of the results.

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